Structural and reduced-form modeling and forecasting with application to Armenia

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Karen Poghosyan

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Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op woensdag 26 september 2012 om 16.15 uur door

Karen Poghosyan,

geboren op 28 januari 1970 te Yerevan, Armenië.

Promotor: Prof. Dr. J.R. Magnus
Copromotor: Dr. O. Boldea

To my wife Lianna and my son Ruben

Preface

This thesis is based on the following three papers:

Chapter 2: Poghosyan, K. and O. Boldea (2012), Structural versus matching estimation: Transmission mechanisms in Armenia, submitted for publication.

Chapter 3: Poghosyan, K. and J.R. Magnus (2012), WALS estimation and forecasting in factor-based dynamic models with an application to Armenia, *International Econometric Review*, 4, 40–58.

Chapter 4: Poghosyan, K. (2012), Factor model versus DSGE model: An out-of-sample forecast comparison.

The views expressed in the thesis do not necessarily reflect the views of the Central Bank of Armenia.

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Contents

Chapter 1

Introduction

In the econometric literature various time-series analysis methods have been developed to forecast economic variables. Among these methods, Box and Jenkins' (1970) univariate time-series analysis and forecasting is especially noteworthy, and has remained an important tool in the analysis and forecasting of univariate time series for a long time. It is still used as a comparative benchmark for other alternative forecasting methods. Extending the univariate framework, methods have been developed for the analysis and forecasting of multivariate time series, particularly unrestricted VAR and Bayesian VAR, which have been popularized by Litterman (1986). Unfortunately, traditional univariate and multivariate forecasting models have a limited ability to forecast, because they can not accommodate a large number of time series in the forecasting model. For practitioners from central banks and other government institutions it is important to have models which can deal with large data sets. This is because central banks operate and analyze thousands of macroeconomic indicators, each of which can provide important information and therefore could help forecasters to produce more accurate forecasts. Forecasting models with large data sets have an important advantage compared to traditional models, because potentially useful information is not neglected.

As a result we have witnessed a continuous increase in the number of papers dealing with factor models during the last decade. Regarding the development of the methodology we mention, in particular, Stock and Watson (2002) and Forni et al. (2000, 2003). While Stock and Watson employ a static principal component model for determining the factors, Forni et al. use dynamic principal components. Both use the factor model and hence describe the dynamics of the economy by using only a few unobservable components that can be extracted from a large number in the initial data set. There are many applications of factor-based dynamic models for forecasting macroeconomic variables, most prominently: Stock and Watson (2002), Artis et al. (2002), Forni et al. (2003), Schneider and Spitzer (2004), Matheson (2006), and Schumacher (2007). The main findings of these applications are that forecasts generated by factor-based dynamic models are superior compared to the traditional benchmark univariate AR and multivariate VAR models.

During the last few decades several competing models have been developed, from business cycle models to the more recent dynamic stochastic general equilibrium (DSGE) models, which include nominal and real rigidities as more realistic descriptions of the macroeconomic environment. The DSGE model is a general equilibrium model, because the main variables of interest are endogenous and depend on each other. It is stochastic, because random shocks affect each endogenous variable, and it is possible to use the model to derive measures of uncertainty in the underlying baseline forecasts (Berg et al., 2006). Estimated DSGE models are now widely used for empirical research in macroeconomics as well as for monetary policy analysis at Central Banks. Such models are often derived from microeconomic foundations. The DSGE model was initially developed for analyzing monetary policy transmission mechanisms under various shocks, and appears to provide admirable descriptions of business cycle dynamics and the effects of various economic shocks on the economy (Smets and Wouters, 2007; Christiano et al., 2005). DSGE models are now increasingly used by Central Banks and other policy-making institutions to aid policy discussions (Tovar, 2008). In addition, the DSGE model is now also used for forecasting purposes. For example, Smets and Wouters (2004) estimated a medium-scale DSGE model using a Bayesian approach and argued that the DSGE model is able to generate better forecasts than unrestricted VAR. Del Negro and Schorfheide (2004) used DSGE priors in a Bayesian VAR model and provided supportive results for the structural model. Liu et al. (2010) used a similar DSGE model with the error terms specified as VAR (Ireland, 2004), and showed that this model can outperform a classical VAR. Adolfson et al. (2008) showed that open-economy DSGE models can compete well with reduced-form models. Alpanda et al. (2011) obtained results which indicate that the DSGE model generates forecasts that are competitive with Bayesian VAR, classical VAR, and random-walk models, especially for short horizons, and adds statistically significant information to combined forecast measures.

Given this background, it seems useful to conduct a comparative analysis among various estimation and forecasting methods both within a particular type of model and between various forecasting models, particularly between the factor model and the DSGE model. This then is the main aim of this thesis. We choose the factor model and the DSGE model because they represent two opposite forecasting philosophies. To conduct comparative analysis we use quarterly data of actual macroeconomic Armenian time series from 2000 to 2010 (46 quarters). This data set comprises information on national accounts data, consumer prices and exchange rate data, financial and monetary policy data, and international economic indicators.

The thesis is based on three papers (Chapters 2–4), and it attempts to make an empirical contribution to the macroeconomic time-series modeling and forecasting literature. The results of the thesis should also be of interest to practitioners from Central Banks and other government institutions where forecasting methods are frequently used.

In Chapter 2 we analyze a structural model for forecasting key macroeconomic variables. We discuss closed- and open-economy model equations. The estimation of the models can be achieved via direct or indirect inference. The direct inference approach is to estimate the structural model via e.g. GMM and use the resulting estimates directly to generate impulse response functions and predict the reactions of the model to various macroeconomic shocks. The indirect inference approach is to generate a reduced form from the structural model, determining the implied theoretical impulse response functions which are then matched to the actual impulse responses, e.g. minimum distance estimation (MDE). Most papers consider structural estimation or reduced-form estimation separately. The main contribution of this chapter is to combine the two, in order to learn more about the structure of economy and its response to various shocks. In this chapter we use valid and relevant information criteria, recently proposed by Hall et al. (2012). These criteria allow us to select such impulse responses that not only provide more reliable estimators, but also indicate valid and relevant portions of the model, where validity and relevance refers to an accurate description of the transmission of shocks into the economy.

In Chapter 3 we discuss the factor-based dynamic model for forecasting key macroeconomic variables. But in contrast to traditional model selection and estimation methods we now use model averaging approaches, particularly the well-known Bayesian model averaging (BMA) and the recently developed weighted average least squares (WALS) method (Magnus et al., 2010). Both methods propose to combine frequentist estimators using Bayesian weights. The theoretical advantage of using the model averaging approach is that model selection and estimation (or forecasting) are treated as *one* procedure, thus avoiding the problem of pretesting. The main purpose of the current chapter is to apply the basic model averaging framework to dynamics and factor extraction, and then to use this dynamic framework to explain and forecast Armenian real GDP growth rate and inflation. In addition we try to compare the BMA and WALS approaches, thus extending the findings in Magnus et al. (2010), where WALS was applied to growth empirics, but without dynamics or lagged dependent variables.

In Chapter 4 we compare two popular forecasting models: DFM and DSGE. We choose these two models because they represent two opposite forecasting philosophies, that is, structural (DSGE is an economic-theory based model) and reduced form (DFM is a factor-based model, mainly data driven). For the comparisons we use out-of-sample recursive and rolling regression simulation experiments. There are only a few papers which carry out out-of-sample forecast experiments between the DSGE and the factor-based dynamic model. We mention Wang (2009), who found that the factor model outperforms DSGE in a short period, but for longer forecasting periods DSGE outperforms the factor model. Gupta and Kabundi (2008) conducted a short-period forecast experiment and concluded that the factor model outperforms DSGE. These results are indicative, but they should not automatically be transformed to other economies. This is because the results are based on country-specific data which may be very different for other economies. For example, developing and developed economies are quite different in the quality and quantity of available statistical data and the nature of how the economy functions. Further analysis to describe the forecasting performances of the factor model versus DSGE model will thus be useful. The main purpose of Chapter 4 is to reconsider the prevailing hypothesis that the factor-based model should be used for short-term forecasting, while the DSGE model should be used for the longer term. To conduct the comparative analysis we apply actual Armenian quarterly macroeconomic time series data from 2000 to 2010. The four models are evaluated based on root mean square error (RMSE) criteria for the one to eight quarters-ahead forecast horizons. The results show that the factor model performs better than DSGE in forecasting our four key macroeconomic variables (real GDP growth rate, inflation, real exchange growth rate, and nominal interest rate). But there is no strong evidence to confirm the prevailing hypothesis. The ex-post forecasting experiments show that factor models can be used both for short- and for long-term forecasting, while DSGE models are better used for long-term forecasting, but not for short-term forecasting.

Our results should be of interest for macroeconomic policy makers in small open economies, not only in Armenia. For example, Chapter 2 features a simple DSGE model, which confirms the success of inflation targeting (with a 4% target and ±1.5% confidence bands) in the decade preceding the crisis, as well as increased forward-lookingness of agents. Chapter 3 suggests that dynamic model averaging techniques may be useful for macroeconomic predictions for real GDP growth and inflation, and Chapter 4 shows that factor models are more accurate for short-term forecasting then DSGE models.

Chapter 2

Structural versus matching estimation: Transmission mechanisms in Armenia

Structural versus matching estimation: Transmission mechanisms in Armenia*

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Abstract: Opting for structural or reduced form estimation is often hard to justify if one wants to both learn about the structure of the economy and obtain accurate predictions. In this paper, we show that using both structural and reduced form estimates simultaneously can lead to more accurate policy predictions. Our findings are based on using new information criteria whose econometric properties allow us to pick for both methods the impulse responses that are valid and relevant for prediction. We illustrate our findings in the context of analyzing the monetary transmission mechanism for Armenia. Based on picking valid and relevant information from both structural and reduced form matching estimation, our findings suggest that the interest rate targeting and the exchange rate channel are well specified and strongly reinforce each other in promoting the recent double-digit growth Armenia experienced before the crisis.

2.1 Introduction

In the last decade, substantial advances in macroeconomic theory and practice were fueled by the widespread use of dynamic stochastic general equilibrium models (DSGE) — see *inter alia* Rotemberg and Woodford (1997), Clarida et al. (1999), Woodford (2003), Smets and Wouters (2005, 2007) and Galí (2008).

*We are grateful to an anonymous referee and to Pavel Čížek, Jakob de Haan, Tobias Klein, Jenny Ligthart, Jan Magnus, Damjan Pfajfar, and Lorenzo Pozzi for useful comments.

These models, known as new Keynesian models, have been used intensively by the main central banks for modeling macroeconomic fluctuations and for prediction. Because they are derived from microeconomic foundations and incorporate key nominal rigidities such as price rigidities, they are capable of quantifying the key monetary transmission mechanisms and thus of guiding policy makers in implementing adequate macroeconomic and monetary policies.

The estimation of new Keynesian models can be done via direct or indirect inference. The direct inference approach is to estimate the structural model via e.g. generalized method of moments (GMM), and use the resulting estimates directly to generate impulse response functions and predict the macroeconomic reactions to various shocks. The indirect inference approach is to generate from the structural model a reduced form, determining the implied theoretical impulse response functions which are then matched to the data via e.g. minimum distance estimation (MDE). Various methods for direct and indirect inference have been implemented by *inter alia* Braun (1994), Christiano et al. (2005), DiCecio (2005), Boivin and Gianoni (2006), Uribe and Yue (2006), Jorda and Kozicki (2007), Dupor et al. (2009), and Altig et al. (2011).

Misspecification in the structural model as well as using too many impulse responses can lead to biased estimates and misleading policy conclusions for both methods. Hall et al. (2012) address this concern by proposing a method to pick impulse response functions (IRFs) that are based on valid and relevant information. The picked IRFs not only provide a more reliable estimator, but also indicate valid and relevant portions of the model, where validity and relevance refer to accurate description of the transmission of shocks into the economy.

This paper is, to our knowledge, the first study to use the methods in Hall et al. (2012) in the context of both structural and reduced form estimation, with the scope of pin-pointing valid and relevant information for policy makers in terms of both economic structure and shock transmissions.

The methods proposed in Hall et al. (2012) are especially relevant for developing countries, where there is not enough data for accurate estimation of a full-scale nonlinear DSGE model. An interesting example of a developing country where such devices are valuable is Armenia. In the decade preceding the crisis, Armenia witnessed successful disinflation and double-digit economic growth. As pointed out by Mkrtchyan et al. (2009), the fiscal consolidation undertaken in the late 1990s played a critical role in reducing inflation, and so did a recent much sounder monetary policy based on targeting inflation through interest rates rather than monetary aggregates.

As for most emerging economies, we find that for Armenia, the interest and exchange rate channels are the main policy transmission channels. The interest rate channel has strengthened due to the official introduction of inflation targeting in 2006, when monetary aggregates became increasingly difficult to target due to the large inflow of cash remittances from Armenians living abroad. Via an open economy New Keynesian model, our paper quantifies the inflation targeting mechanism and its effectiveness in conjunction with the large appreciation of the nominal exchange rate of dram.[1]

Most papers consider structural estimation or reduced form estimation, but not both. Our main contribution is to combine the two with the scope of both learning about the structure of the economy and its responses to various shocks. We take advantage of econometrically rigorous misspecification checks to point to the valid and relevant shock transmission mechanisms.

We start by introducing a small scale New Keynesian open economy model to quantify the exchange-rate pass-through to output and prices. We estimate the model both directly (structural estimation) and indirectly (reduced form matching estimation), and use the new methods proposed by Hall et al. (2012) to check for misspecification. We find that inflation targeting, reinforced by a small exchange-rate pass-through to prices, has been very successful in Armenia in the recent decade. Our study is in line with the findings of Mkrtchyan et al. (2009), Bordon and Weber (2010) and El-Ganainy and Weber (2010), but due to picking valid and relevant IRFs, we are able to show that the exchange rate and interest rate shocks are well-specified in our model. Additionally, we find that even though agents are forward-looking and inflation targeting was successful in the last decade, the dynamics of output may be more subtle, possibly due to cash remittances and large monopolies in the import sector that prevent a higher exchange-rate pass-through. Inflation targeting in conjunction with forward-lookingness are extremely relevant for the macroeconomic performance of Armenia in the recent crisis period, but we find that more research is needed to uncover the true response of the economy to output and inflation shocks.

Our paper is organized as follows. Section 2 introduces the open economy New Keynesian model. In Section 3 we give a brief on Armenia and we summarize the

[1]Dram is the national Armenian currency.

construction of our data-set, which is then detailed in Appendix A. Section 4 reports and interprets the estimation results for structural and IRF matching estimation. In Section 5, we check for misspecification via the methods in Hall et al. (2012), which we extend to structural estimation as well. This section also contains the policy implications based on impulse response functions that contain valid and relevant information. Section 6 concludes. Appendix A is a data appendix, and Appendix B contains graphs of our dataset and of the valid and relevant IRFs.

2.2 Structural model

Armenia is a small open economy — population of approximately 3 million people and trade openness degree of about 55% in 2005 prices, during the last decade (Penn World Table). To understand the macroeconomic dynamics in Armenia, we use a simple New Keynesian open economy model with rational expectations. As is common practice in macroeconomics, the New Keynesian model we use is derived from a representative's agent intertemporal utility maximization problem, in the presence of external habit persistence, with staggered wages and hybrid monetary policy (hybrid here means both forward and backward looking). Cho and Moreno (2003) argue that such a parsimonious model is rich enough so that the dynamic path of inflation, output gap and interest rate can be clearly explained in terms of structural parameters. We make no such claims, because as Ruge-Murcia (2007) points out, structural and matching estimation can suffer from misspecification, weak identification and/or stochastic singularity. We acknowledge that our model may be misspecified, but we start with it as a benchmark, then check which part of the model may be misspecified. For modeling, we closely follow Berg et al. (2006).[2]

In the open economy model, output gap depends on aggregate demand, thus on the real interest rate and the real exchange rate, as well as past and future expected output:

$$y_t = \mu E_t y_{t+1} + (1-\mu) y_{t-1} - \phi r_t + \kappa e_t + \epsilon_t^y \tag{2.1}$$

where r_t is real interest rate, e_t is the real exchange rate (defined as units of home currency per one unit of foreign currency). Here, ϵ_t^y is a demand shock with mean zero and variance σ_y^2. The key parameters of interest are the monetary transmission

[2]Note that supply shocks enter mainly our model through the Phillips curve. This simplification is mainly employed for tractability, and several aspects of the supply side could be introduced in a richer model.

mechanism parameter ϕ, and the effect of competitiveness on home demand, κ. Here, $\mu \in (0, 1)$, indicating that part of the households are forward looking, $\phi > 0$ indicating that a decrease in interest rates should have expansionary effects, and $\kappa > 0$, signaling that increased competitiveness abroad should increase home demand. As mentioned in Berg et al. (2006), if $(\phi + \kappa)$ is small relative to $(1 - \mu)$, we expect significant lags in the transmission of monetary policy, since the inertia in output will prevent monetary policy effectiveness. On the other hand, if it is relatively high, then the monetary policy transmission mechanism is swift.

Following Berg et al. (2006), we define the open economy New Keynesian Phillips curve as depending on expected and lagged inflation, the output gap and the real exchange rate gap.

$$\pi_t = \delta E_t \pi_{t+1} + (1 - \delta)\pi_{t-1} + \lambda y_t + \tau(e_t - e_{t-1}) + \epsilon_t^{\pi} \tag{2.2}$$

The presence of backward and forward components of inflation is justified in Galí and Gertler (1999), and reflects a Calvo price-setting mechanism with sticky prices. Here $\delta \in (0, 1)$, reflecting the fraction of firms that reset their prices based on expectations. Also, $\lambda > 0$, indicating a positive trade-off over the cycle between inflation and output gap. As found in several studies — see e.g. Gali and Gertler (1999) and Zhang, Osborn and Kim (2008), this trade-off is weaker for recent decades, and so we expect this coefficient to be small.

This Phillips curve is appropriate for Armenia, as it also reflects the idea that the fundamental role of monetary policy is to provide a nominal anchor for inflation; this is reflected in the fact that the backward- and forward-looking coefficients on inflation add up to one. The parameter τ represents the real exchange rate pass-through to prices, which we expect to be low for Armenia: the nominal exchange rate appreciated approximately 40% in 2004-2007, followed by only a 5% drop in imported good prices. This slow exchange rate pass-through is usually attributed to nominal rigidities in the imported good sector and arises from inefficient distribution networks, but also due to a large proportion of monopoly retailers that use domestic labor as an input, making prices even less responsive to exchange rate movements — see Mkrtchyan et al. (2009). Thus, $\tau > 0$ and should be small. As in Berg et al. (2006), we use the real exchange rate rather than the nominal exchange rate; such an equation can be obtained from a consumption smoothing model with opening of the capital market — see e.g. Razin and Yuen (2002) for a theoretical justification.

As before, ϵ_t^π denotes an aggregate supply structural shock with mean zero and variance σ_π^2.

The third equation specifies the exchange rate path. Unlike in Berg et al. (2006), the real exchange rate dynamics is a linear expected exchange rate rule, known as "partially uncovered interest parity" — see Plasmans et al. (1998) and De Grauwe and Vansteenkiste (2007). Following Berg et al (2006), we use the real exchange rate rather than the nominal exchange rates, allowing for price disparities to be reflected in the error term. Unlike Mkrtchyan et al. (2009), we do not impose uncovered interest parity (UIP), as it would require perfect capital mobility and complete financial markets, features that are unlikely to hold for developing countries like Armenia. We assume that the real exchange rate depends on the expected and lagged real exchange rate as well as the differences between home and foreign real interest rate gap:

$$e_t = \varphi E_t\, e_{t+1} + (1-\varphi)e_{t-1} - \eta(r_t - r_t^*) + \epsilon_t^e, \tag{2.3}$$

where r_t^* is the international real interest rate and ϵ_t^e is a real exchange rate structural shock with mean zero and variance σ_e^2. Here, $\eta > 0$, so the expected real exchange rate gap is partly covered by the previous and expected future gaps - $\varphi \in (0,1)$, and partly by the exchange rate difference. Despite the widespread use of UIP, estimates for η are not one as UIP predicts, but usually small and quantitatively similar for OECD countries - Plasmans et al. (1998) and ASEAN countries - Boldea et al. (2012). We show in Section 7 that the exchange rate dynamics is well-specified across all models and identification strategies we use.[3]

We close the model by specifying a monetary policy rule for Armenia, which targets inflation as well as output. Even though the inflation targeting regime was introduced in 2006, implying as in Bordon and Weber (2010) a possible parameter change in β, there is strong evidence that there was inflation targeting before. Our short data horizon does not allow us to reliably identify potential change-points in the interest rate rule, so we stick to a stable-parameter interest rate rule:

$$i_t = \rho i_{t-1} + (1-\rho)(\beta E_t \pi_{t+1} + \gamma y_t) + \epsilon_t^i \tag{2.4}$$

[3]Alternatively, we could use models involving risk premia. We chose this model because for developing countries, risk premia seem to introduce large volatilities that are more difficult to tackle within a simple model.

with ϵ_t^i an interest rate shock with mean zero and variance σ_i^2. The parameter $\rho \in (0,1)$ indicates the degree of interest rate smoothing.[4] Note that if there is no shift in the interest rate trend, then the equation (2.4) can be rewritten with detrended nominal interest rates i_t.[5]

The next section details the construction of our dataset and its main features.

2.3 Brief on Armenia and data

According to the CIA World Factbook, under the Soviet Union, Armenia developed a modern industrial sector, but since then has switched to placing emphasis on small-scale agriculture. It has progressed in introducing many economic reforms, including privatization, solid fiscal policies, price reforms, but its narrow export base and pervasive monopolies in main business sectors make Armenia still vulnerable to a global downturn. Nevertheless, in the decade before the crisis, it has been successful in slashing inflation to single digits and in promoting a double-digit growth, due to sounder macroeconomic policies, in conjunction with a booming construction sector and the cash remittances from abroad. The sharp trade imbalance has been financed by international aid, and Armenia, joining the World Trade organization in 2003, has made large improvements in tax and customs administration.

The central bank of Armenia, targeting first monetary aggregates and the exchange rate, has switched in the last decade to inflation targeting through interest rates, as managing the monetary aggregates has been proved ineffective due to the large inflow of cash remittances from abroad. Even though the inflation targeting was officially introduced in 2006, there is evidence that the central bank has been targeting inflation much earlier — see e.g. El-Ganainy and Weber (2010). The inflation target was initially 3% for 2006, and changed only once in 2007; from 2007 onward, it is maintained at 4% with a confidence band of ± 1.5% around it, reflecting the need to maintain credibility. The credibility of the monetary authority has been increasing over the recent years due to its successful policies. In this paper,

[4] As pointed out in Rudebusch (2002) and Gorter (2008), the magnitude of this parameter may be overstated if the errors are autocorrelated. We test and find no autocorrelation in the errors of all equations over the sample period, so the parameter estimate for ρ can be legitimately interpreted as interest rate smoothing.

[5] Even though Armenia has switched to inflation targeting in 2006, our small sample does not permit us to reliable test for a trend shift in the interest rates. However, visual inspection of the data does not seem to indicate such a shift, so we work with detrended interest rates.

we quantify the strength of the monetary transmission mechanisms through both structural and reduced form estimation. The structural models are presented in the next section.

Our dataset comprises monthly data on Armenian key macroeconomic indicators, from January 2001 to December of 2008, and it is computed using information provided publicly by the Armenian Statistical Service Agency. We construct two monthly real GDP series that are not publicly available but can be proxied using the data at hand. To our knowledge, this is the first study that constructs and uses monthly data for Armenia. Our choice of monthly data is guided by our desire to use larger samples and the availability or reliable monthly data on GDP for different sectors; thus, we claim that our study is less prone to small sample problems compared to e.g. Mkrtchyan et al. (2009).

Based on the available data, we construct two proxies for the monthly real GDP. The first proxy is computed using constant 2009 prices as the base, but ignoring the officially published quarterly real GDP. The second measure adjusts the first for the implied official quarterly real GDP growth, reported at constant 2005 prices, which seems to be a more stable year. The computations of these two measures along with the other data below are detailed in Appendix A. The two measures are not too different, as can be seen from Figure 2.1 in Appendix B. There is a sharp drop in the last quarter of 2008 in the second measure compared to the first, but our computations indicate that this doesn't affect the results too much.

As for prices, we use inflation in the CPI index, whose calculation can be found in Appendix A. The plots in Figure 2.1 indicate that inflation has been kept down to single digits quite successfully during the recent decade.

The Central Bank of Armenia main policy instruments is the repo (repurchase agreement) interest rate. Real exchange rates (in dollars per Armenian dram) and nominal interest rate data are published by the Central Bank of Armenia. Plots of the interest rate and real exchange rate gap data are in Figure 2.1. We work with detrended interest rate but chose not to detrend inflation, so that its path with respect to the target can be easier analyzed. While detrending interest rates but not inflation is in general likely to distort the relationship between the two and affect the conclusions about the effectiveness of monetary policy[6], we maintain that this practice is innocuous for our sample, as the inflation trend is very close to zero.

[6]We would like to thank an anonymous referee for pointing this out.

We restrict our attention to the sample period 2001-2008 for two reasons. First, as Dabla-Norris et al. (2007) show (see their Figure 2), CPI inflation was very high and volatile before 2000, reaching levels of approximately 25% in 1998. Greater exchange rate flexibility was introduced only around 2000, allowing to bring down inflation to single digits, and a commitment to price stability has not been officially made until the previous decade. This indicates that a Taylor rule may be inappropriate before 2001, which motivates the start of our dataset. We end our dataset in 2008 due to the fact that the onset of the financial crisis and the presence of large fluctuations in real quarterly GDP (53% in the first quarter of 2012 compared to previous quarter), compound with spillovers from the Eurozone crisis, have driven the Central Bank of Armenia to interest rates of around 8% in May 2012 (see Minutes of June 2012 meeting, www.cba.am). Intuition from the recent crisis indicates that such high interest rates cannot be rationalized with sensible inflation targeting, since inflation in May 2012 was around 0.5%, while the current inflation target is 4% with $\pm 1.5\%$ confidence bands. Thus, we believe that if we estimated a model extending our dataset to the recent periods, the evaluation of inflation targeting and all estimates would be inaccurate both due to breaks and high volatility. These issues cannot be properly addressed in our econometric framework as they would invalidate the impulse response analysis we conduct, as well as the methodology we use to compare the structural to the reduced form estimation.

All time-series except inflation are in percentage deviation from their gaps, and so have been de-trended using the Hodrick-Prescott filter. Using the above described data set, we quantify the monetary transmission mechanisms in the next sections.

2.4 Estimation results

2.4.1 Structural estimation by GMM

Based on the two output gap measures, we estimate the open economy model in (2.1)-(2.4) via iterated GMM.

A possible pitfall of using GMM with lags of variables as instruments is that they may be weak — see e.g. Fuhrer and Rudebusch (2004) for concerns about the output equation, and Ma (2002) and Mavroeidis (2004) for concerns about the Phillips curve. We assess various instruments sets via the Cragg and Donald (1993) statistic using Stock and Yogo's (2005) critical values. We chose the set of instruments which is strongest according to Stock and Yogo's (2005) test, $z_t' = (y_{t-1}, y_{t-2}, y_{t-3}, \pi_{t-1}, \pi_{t-2}, \pi_{t-3}, e_{t-1}, e_{t-2}, i_{t-1}, i_{t-2})$.[7]

Thus, the moment conditions are $E[\epsilon_t \otimes z_t] = 0$, with $\otimes$ denoting the Kronecker product, and $\epsilon_t = (\epsilon_t^y, \epsilon_t^\pi, \epsilon_t^e, \epsilon_t^i)'$. We assume rational expectations, implying that z_t, reflecting the information set at time $t-1$, is uncorrelated with future expectations of variables, namely $E_t\pi_{t+1}, E_t y_{t+1}, E_t e_{t+1}$. Hence, the moment conditions can be written in terms of the original variables rather than expectations; for example, the moment conditions for ϵ_t^y can be written as:

$$\begin{aligned} E[\epsilon_t^y z_t] &= E[y_t - \mu E_t y_{t+1} - (1-\mu) y_{t-1} + \phi r_t - \kappa e_t] z_t \\ &= E[y_t - \mu y_{t+1} - (1-\mu) y_{t-1} + \phi r_t - \kappa e_t] z_t = 0. \end{aligned}$$

The results in Table 2.7 are very consistent across the two different measures of real GDP, despite the sharp drop in the second measure of GDP at the end of the period. Some of the parameter estimates are closely in line with those of other developed or developing countries, others reveal unique features of the Armenian economy. Since the estimate of ϕ is strongly significant, we find that the interest rate in Armenia does influence output directly. The estimate is not large, but much larger than usually found for US — see Cho and Moreno (2003), indicating that even if the objective of monetary policy is mostly inflation targeting, as seen from the interest rate equation estimates, there is potential for the monetary policy to stabilize output as well.

For the output equation, we find that the intertemporal elasticity of substitution in consumption, according to the estimates based on real GDP 2, is — see Cho and Moreno (2003) for formula derivation — $1/\sigma = \phi/\mu \sim 0.05/0.5 = 0.1$. This implies that Armenian consumers are impatient, in line with the majority of population having small wages — see Guvenen (2006). Also, habit persistence h, defined as $1/\phi = \sigma(1+h) - h$ — see Cho and Moreno (2003), is approximately $h \sim 1.11$. This implies that people's consumptions choices are strongly enrooted in habit, unlike findings for some EU members — see e.g. Flavin and Nakagawa (2008).

The estimate of λ indicates a flat Phillips curve. This flatness is a well-known finding for many economies — see e.g. Galí and Gertler (1999) for US, Mihailov et

[7] Results with various instrument combinations with first, first up to second, and first up to third lags of are available upon request from the authors. We also test for autocorrelation in the errors and find no further evidence of autocorrelation in our data, indicating that the moment conditions are likely to be well specified for z_t.

Table 2.1: GMM estimates

	Real GDP 1	Real GDP 2
	Output equation (2.1)	
μ	0.5483***	0.5677***
ϕ	0.0162***	0.0432***
κ	0.0002	0.0012*
	Phillips curve (2.2)	
δ	0.5678***	0.5661***
λ	0.0073	0.0044
τ	0.0319***	0.0331***
	Exchange rate rule (2.3)	
ϕ	0.5597***	0.5359***
η	0.1879***	0.1416***
	Interest rate rule (2.4)	
ρ	0.6444***	0.7870***
β	2.2341***	2.0544***
γ	0.0836***	0.0165***

Note: The superscripts *, ** and *** are used to indicate significance at the 10%, 5% and 1% level, respectively.

Table 2.2: Weak Instrument Diagnostics

	F statistic real GDP 1	Reject 10% level	F statistic real GDP 2	Reject 10% level
Output equation (2.1)	22.5	Yes	19.6	Yes
Phillips curve (2.2)	16.5	Yes	16.3	Yes
Exchange rate rule (2.3)	6.33	No	11.0	Yes
Interest rate equation (2.4)	0.62	No	0.41	No
System (2.1)-(2.4)	**14.9**	**Yes**	**13.4**	**Yes**

al. (2011) for Poland, Hungary, Slovakia, Latvia, Lithuania, Cyprus, Malta, Czech Republic, Slovenia, Bulgaria, where some estimates are even negative. Galí and Gertler (1999) argue that output gap is not proportional to real marginal cost, but real marginal cost better accounts for direct productivity gains on inflation, and so it should replace output gap in the Phillips curve. On the other hand, real marginal cost is also unobserved, and other authors, e.g. Ruud and Whelan (2005) argue that the current practice of replacing marginal cost with average unit labor cost has little theoretical foundations. We do not use marginal cost proxies here due to data limitations.

El-Ganainy and Weber (2010) estimate a slightly different specification for the open-economy Phillips curve for Armenia, and find that output gap is significant; their results might be influenced by the less efficient single equation estimation and by the use of data from the recent financial crisis. They also find that inflation is mostly backward looking, while we find that the success story of Armenia in reducing inflation to single digits is attributable to inflation targeting combined with forward-looking behavior. However, our results show that the backward looking component is almost equally important. Similar findings can be found in Berg et al. (2006) for Canada, and Zhang et al. (2008) for US. Mkrtchyan et al. (2009) calibrate the forward-looking parameter to 0.65, assuming slightly less inflation inertia but the IRFs are qualitatively comparable to ours, reinforcing the effectiveness of inflation targeting through forward-lookingness.

As for the interest rate, even though inflation targeting is not explicit until 2006, and the target changed once over the sample period, in 2007, while our data limitations do not allow us to consider a moving target or split the sample, our large and significant estimate for β across the two real GDP measures implies that inflation targeting is actively employed over the period, whether explicitly or implicitly. We notice that despite the inflation targeting, the interest rate exhibits high inertia. This is not surprising, as policy makers maintain credibility by not spooking the markets with large interest rate swings. We find that the objective of price stability precedes that of output stability. Output stability is relatively less important, but also seems to be taken into account. This is important, as the Armenian central bank is forced to dampen the effect of large cash remittances from abroad, which are part of the measured GDP.

As for competitiveness, the parameter κ is close to zero, even though significant for real GDP 2. This implies that the direct competitiveness has a small impact on output. On the other hand, the estimates for τ are significant and slightly larger, indicating that the exchange rate pass-through to prices does happen but is incomplete. This is in line with the fact that during 2004-2007, the nominal exchange rate appreciated by more than 40% but was accompanied by a less than 5% decline in imported good prices; thus, most importing Armenian firms take into account domestic unit labor costs in their pricing decisions. According to Karam and Pagan (2008), Canada exhibits an incomplete pass-through of almost the same magnitude.

There is widespread empirical evidence that the uncovered interest parity (UIP) doesn't hold — see the comprehensive surveys of Froot and Thaler (1990), Lewis (1995) and Engel (1996). We reconfirm this finding for Armenia, where the expected exchange rate differentials seems to be partially uncovered by the interest rate differentials and predominantly by their previous values.

Overall, we find that the central bank sets a high weight on targeting inflation, and that the exchange rate pass-through to output and prices is incomplete, but the exchange rate rule acts to reinforce inflation targeting as a monetary policy decision. These findings are consistent across the two measures of real GDP. The monetary transmission mechanism, while slow, seems to work well for Armenia. The results in Table 2 also indicate that while individual tests can suggest weak identification given our instrument set, the more rigorous overall test indicate strong identification.

Our results are based on a parsimonious model, which is potentially misspecified. In the next sections, we perform IRF matching estimation to provide misspecification checks via picking valid and relevant impulse response functions.

2.4.2 IRF matching estimation

Impulse response matching estimation is frequently used in different forms and with different methods of estimation — see Ruge-Murcia (2007) for a detailed account. Here, we consider one of the most popular matching estimation procedures, the vector autoregression (VAR) based IRF matching. The parameter estimates are obtained by minimizing the distance between the sample IRFs obtained by fitting a VAR(1) to the actual data and the theoretical IRFs generated by the New Keynesian model. We use a VAR(1) instead of a larger order because this arises as the rational expectations solution of our model.

In two recent papers, Dridi et al. (2007) and Hall et al. (2012) present a comprehensive statistical framework for estimating parameters of a structural model by matching moments using a binding function obtained from a reduced form model. Using their terminology here, the New Keynesian model is the structural model, the VAR(1) is the reduced form model, and the IRFs are the binding functions. They allow for model misspecification and group parameters into three categories: focus parameters (those we are interested in), estimated nuisance parameters and calibrated nuisance parameters. Since the structural model may be misspecified, an important question is whether it partially or fully encompasses the reduced form model, meaning that even in the presence of misspecification, the minimum distance estimation based on the binding function nevertheless yields consistent estimators of the focus parameters.

This paper focuses on the monetary transmission mechanism for Armenia as an open economy. We thus take the open economy model, and define the focus parameters to be $(\phi, \kappa, \lambda, \beta, \gamma)$, describing the influence of interest rates and exchange rates on output, the slope of the Phillips curve whose structural estimate might suffer from misspecification bias, and the relative weights monetary policy sets on price and output stability. We consider η as a nuisance parameter, that we have to estimate to confirm the UIP violation; the rest of the parameters we regard as calibrated nuisance parameters and set them equal to their structural estimates. We also set the variance of MDE errors as it is implied by the structural estimates $\sigma_y^2, \sigma_\pi^2, \sigma_e^2$ and σ_i^2.

By matching all the impulse response functions at a horizon of 20 months using minimum distance estimation, we obtain the estimates for the focus and estimated nuisance parameters; the results are in Table 2.3 below.

One of the most striking results in Table 2.3 is that ϕ is much larger for the reduced form estimates, indicating that monetary policy may have a (much) larger influence on output than the initial structural model estimates indicates. We also note that the Phillips curve seems to be less flat if we match impulse response functions, and the trade-off between inflation and output even becomes significant under MDE_2. Inflation targeting is consistently the primary objective of monetary policy. While MDE_1 estimates imply a higher weight on output stability, under MDE_2, output stability seizes to be a significant monetary policy goal.

Most results are qualitatively the same across different estimates, but their quantitative differences indicate that the output and inflation responses may be

Table 2.3: VAR and MDE estimates

	GMM_1	GMM_2	MDE_1	MDE_2
	Output equation (2.1)			
ϕ	0.0162	0.0432***	0.1345***	0.0545
κ	0.0002	0.0012*	0.0510***	0.0112
	Phillips curve (2.2)			
λ	0.0073	0.0044	0.0450	0.0350***
	Exchange rate rule (2.3)			
η	0.1879***	0.1416***	0.1100***	0.1000***
	Interest rate rule (2.4)			
β	2.2341***	2.0544***	1.8250***	2.2500***
γ	0.0836***	0.0165***	0.1500***	0.0450

Note: the * and *** superscripts are used as in Table 2.7, while the subscripts $_{1,2}$ indicate estimation using real GDP 1 or 2.

misspecified, and finding such misspecifications is important for accurate policy recommendation. Having potential misspecification implies that the parameters we fixed may be biased, and this, while it will affect the impulse response matching estimation as a whole, it will not affect "right" — meaning valid and relevant — impulse response functions.

The next subsection explains the notion of valid and relevant IRFs, uses the methods in Hall et al. (2012) to pick those among all IRFs, and discusses the implications of these choices for monetary policy.

2.5 Selecting valid and relevant IRFs

The motivation for checking for misspecification via selection of valid and relevant IRFs in MDE is best seen by drawing a parallel to moment selection in GMM. When we perform GMM estimation, we implicitly assume we have "right" moments: those that are valid, meaning that the population moment condition holds, and relevant, meaning that they add new information, thus contributing to more efficient estimators. Otherwise, one can pick the valid and relevant moments via moment selection criteria — see Hall et al. (2007).

Similarly, Hall et al. (2012) propose information criteria for picking valid and relevant IRFs to estimate the focus and nuisance parameters. They pick IRFs that are valid, meaning correct even though the calibrated (fixed) nuisance parameters are misspecified, and relevant, meaning that they increase the efficiency of the focus parameter estimators.

In this paper, we do not attempt to pick IRFs across horizons as we assume that the central bank has a certain fixed horizon length $H = 20$ for prediction. This is reasonable for a developing country like Armenia. We focus on picking the valid and relevant IRFs to various shocks. In the open economy model (2.1)-(2.4), we have four equations, thus four shocks, which can be taken one, two, three at a time or all four together. For each of these, we calculate the valid impulse response selection criterion (VIRSC) and the relevant impulse response selection criterion (RIRSC).

To define VIRSC and RIRSC, we need to introduce some notation. Let $n_Y = 4$ be the number of shocks (equations) in the open economy model. Define $\alpha = g(\theta, \eta, \psi)$ to be the $n_Y^2 H \times 1$ vector of impulse response functions implied by the set of structural parameters (θ, η, ψ) from the structural model (2.1)-(2.4), to which the VAR(1) OLS estimated impulse response functions $\hat{\alpha}$ are matched. In both the implicit theoretical impulse responses α and the estimated impulse responses $\hat{\alpha}$, the nuisance parameters that are not estimated are fixed at their estimated structural values, $\psi = \bar{\psi}$.

To check for misspecification, we allow for the possibility that not all $n_Y^2 H \times 1$ IRFs are valid and relevant for MDE estimation. For selecting the valid and relevant IRFs, as in Hall et al. (2012), let c, an $n_Y \times 1$ selection vector, index the IRFs that are included for MDE for each horizon. Denote $\alpha(c) = g(\theta, \eta, \bar{\psi}, c)$ the selected theoretical IRFs, and $\hat{\alpha}(c)$ their estimated counterparts. Then, if the n^{th} element of c equals one, and the rest are zero, this implies that only the n^{th} element of $\alpha(c)$, respectively $\hat{\alpha}(c)$, is included in the MDE.

Using this notation and letting T be the sample size, the MDE estimator for selected IRFs can be defined as:

$$(\hat{\theta}(c), \hat{\eta}(c)) = \text{argmin}_{\theta,\eta} Q_T(\theta, \eta, c)$$

where:

$$Q_T(\theta, \eta, c) = [\hat{\alpha}(c) - g(\theta, \eta, \bar{\psi})]' \hat{\Omega}_T(c) [\hat{\alpha}(c) - g(\theta, \eta, \bar{\psi})]$$

with $\hat{\Omega}_T(c)$ being an estimate of the inverse of the covariance matrix of the IRFs that were selected through c.

We select the valid impulse response functions by minimizing:

$$VIRSC_T(\hat{\theta}(c), \hat{\eta}(c), c) = Q_T(\hat{\theta}(c), \hat{\eta}(c), c) - |c| ln(T)$$

over all c. This information criterion picks the minimum number of valid impulse response functions needed to minimize the MDE objective function.

The relevant impulse response functions are selected by minimizing:

$$RIRSC_T(\hat{\theta}(c), \hat{\eta}(c), c) = ln(\det\ (\hat{W}_T(\hat{\theta}(c), \hat{\eta}(c), c)\,)) + |c|(lnT)/\sqrt{T})$$

where $(\hat{W}_T(\hat{\theta}(c), \hat{\eta}(c), c)$ is the 5×5 left upper corner sub-matrix of the estimate of the long-run covariance matrix of the selected theoretical IRFs (long-run variance of the focus parameters), ln denotes the natural logarithm and $det(A)$ stands for the determinant of the matrix A. This criterion picks the upper left 5×5 matrix relevant for our focus parameters; we want to minimize a penalized version of its determinant to pick the smallest and thus the most efficient covariance matrix with the minimum number of shocks.

The penalty of both information criteria c are imposed as suggested in Hall et al. (2012) to yield consistent estimators of c for respectively the valid and the relevant impulse response functions.

Subject to the existence of a minimizing selection vector for both criteria, one notices that their asymptotic properties in terms of picking the valid, respectively the relevant information criteria, depend only on having consistent estimates of the parameters θ, η and their asymptotic variance. In other words, they do not depend on the method used for estimating θ, η, and one can also use these criteria by plugging in GMM estimates for θ, η instead of their MDE counterparts. The asymptotic properties of c are the same, as we have a linear model, so all the smoothness assumptions in Hall et al. (2012) are satisfied.

We thus report the information criteria for both GMM and MDE estimates. Table 4 and 5 report the VIRSC, respectively RIRSC for different selection vectors c. Table 6 reports the corresponding selected IRFs group-wise for responses to one, two, three shocks and overall.

Table 2.4: VIRSC values for GMM and MDE generated IRFs

c	GMM_1	GMM_2	MDE_1	MDE_2
$1,0,0,0$	0.449	64.301	1.209	66.293
$0,1,0,0$	0.067	16.412	0.560	21.122
$0,0,1,0$	-0.003	0.044	0.034	0.057
$0,0,0,1$	-0.002	0.374	0.001	0.689
$1,1,0,0$	0.204	0.927	11.112	2.857
$1,0,1,0$	0.289	31.297	0.365	34.640
$1,0,0,1$	0.303	17.680	2.415	14.745
$0,1,1,0$	0.011	37.824	0.036	42.313
$0,1,0,1$	0.463	60.981	1.031	85.308
$0,0,1,1$	0.059	2.655	0.030	3.257
$1,1,1,0$	0.204	0.195	4.211	0.570
$1,1,0,1$	0.050	0.139	15.989	2.986
$1,0,1,1$	0.419	6.529	0.966	5.610
$0,1,1,1$	0.082	113.587	0.157	143.219
$1,1,1,1$	0.049	0.096	7.051	0.975

Table 2.5: RIRSC values for GMM and MDE generated IRFs

c	GMM_1	GMM_2	MDE_1	MDE_2
$1,0,0,0$	-14.0	-19.7	-12.2	-9.3
$0,1,0,0$	-4.0	-6.8	-8.2	-9.2
$0,0,1,0$	-21.8	-20.1	-16.3	-14.3
$0,0,0,1$	-10.6	-8.8	-11.9	-12.7
$1,1,0,0$	0.5	-4.7	-6.4	-6.5
$1,0,1,0$	-14.7	-22.2	-13.1	-10.3
$1,0,0,1$	-3.5	-4.5	-10.6	-7.4
$0,1,1,0$	-6.1	-6.2	-8.5	-9.4
$0,1,0,1$	-2.2	-5.1	-7.6	-6.7
$0,0,1,1$	-15.6	-9.2	-14.2	-9.4
$1,1,1,0$	0.1	-6.8	-6.1	-8.9
$1,1,0,1$	1.7	-1.4	-8.7	-6.1
$1,0,1,1$	-4.2	-5.6	-11.3	-9.6
$0,1,1,1$	-3.4	-2.8	-8.3	-6.2
$1,1,1,1$	1.5	-2.5	-8.3	-10.3

Table 2.6: Valid and relevant shocks

Number of shocks	valid/relevant	GMM_1	GMM_2	MDE_1	MDE_2
1	valid	e	e	i	e
	relevant	e	e	i	e
2	valid	π, e	i, e	i, e	y, π
	relevant	i, e	y, e	i, e	y, e
3	valid	y, π, i	y, π, e	y, i, e	y, π, i
	relevant	y, i, e	y, π, e	y, i, e	y, π, e
all	valid	e	e	i	e
	relevant	e	y, e	e	e

Note: The symbols y, π, e, i indicate that the IRFs of all variables that have been picked w.r.t. to a shock to y, π, e and i, respectively.

The main message of Table 2.6 is that the selected IRFs, similar across different output gap measures and different estimates, are the responses to exchange rate or interest rate shocks. This implies that the impulse responses to an exchange rate or interest rate shock and their transmission into the economy are both valid and relevant despite the fixed parameters $\bar{\psi}$ which may or may not be misspecified. Since we have found that both GMM and MDE qualitatively and quantitatively agree as to the strength of the interest targeting policy in Armenia and its high effectiveness in the last decade, our findings imply that the monetary policy is quite effective when reinforced by the exchange rate channel. Since the exchange rate shock responses are picked as valid or relevant or both, the exchange rate channel reinforces the interest rate channel in the transmission mechanism. On the other hand, we see that the responses to inflation are almost never valid or relevant, implying that the expectations are not entirely anchored as described by a Phillips curve even though the interest rate and exchange rate shocks may influence inflation as described, through indirect channels. The exclusion of the responses to inflation shocks from the valid and relevant IRFs is a robust finding across the GMM and MDE estimates, suggesting that the misspecification may come from the estimates of ρ which are being kept fixed, rather than the rest of the structural model. This is useful for policy makers as it may imply that even though their policies are effective, more credibility may be needed to modify the forward-lookingness of economic agents.

Moreover, picking the overall valid and relevant IRFs allows the monetary policy makers to be better informed about the policy transmission mechanism and its duration. The Appendix B contains the IRFs of all variables to a positive shock in the interest rate and the exchange rate, based on our four estimates (GMM and MDE with each two different output gap measures).

Figures 2.2-2.5 show that an increase in the interest rate reduces output through intertemporal substitution. The real exchange rate drop (appreciation) implies less domestic demand, reducing equilibrium prices and inflation. The monetary policy makers respond to the lower demand and production by reducing the interest rate, which then increases consumption and output, depreciating the real exchange rate. The real exchange rate partial uncovered parity implies further depreciation of the real exchange rate, which returns to the equilibrium but slower than the other real variables. Our findings are qualitatively similar to those in Mkrtchyan et al. (2009), Figure 8, pp. 29. We find that for the MDE estimates, the return to the equilibrium is much faster for output and prices than suggested by the GMM estimates. These differences are best explained by realizing that the pass-through of the exchange rate to prices is much slower for the GMM estimates.

In addition to Mkrtchyan et al. (2009)'s IRFs, we report the IRFs from a shock in the real exchange rate — see Figures 2.6-2.9. We find that a depreciation in the exchange rate has a small but steady impact in changing domestic demand, output and prices. The monetary authority responds to the output increase by increasing the interest rate, which in turn reduces output, causing it to gradually return to equilibrium.

2.6 Conclusions

Opting for structural or reduced form estimation is often hard to justify in the light of potential misspecification. Since both estimations are based on a larger structural model that is unknown, both models can be misspecified, and either can be worse in terms of policy recommendation depending on data at hand — see Ruge-Murcia (2007). In this paper, we do not pick one path, but show that marrying the two can lead to important conclusions about the type of misspecification. To that end, we use the method in Hall et al. (2012) for picking valid and relevant impulse response functions. We extend its use of their method to structural parameter estimates, and point to the location of the misspecification for a dataset pertaining to Armenia.

Our small-scale model for Armenia does not include the large cash remittances from abroad and the impressive boom in the construction sector, because such features are uncommon for developed countries and thus not part of any standard model. Instead of attempting to model such features which would be subject to small-sample estimation issues, we show by means of picking relevant and valid information that a Phillips curve and the open-economy aggregate demand equation may both be misspecified, especially with regard to modeling expectations. But more importantly, we show that, despite the misspecification, the interest rate targeting works through the direct transmission channel, and the exchange rate mechanism, suffering from partial uncovered interest parity, still influences aggregate demand through a small but significant partial pass-through to output and prices.

Picking valid and relevant information is thus useful in highlighting the monetary policy aspects of the Armenian economy that have been solid over the previous decade. We postulate that such methods are useful for policy makers in different countries, because they can pin-point to the source of the misspecification and thus make more accurate policy recommendations, while using information from both structural and reduced form models when both are identified.

2.7 Appendix A: Data

This Appendix details the data availability and construction at monthly frequency. The data we use is freely available from the Armenian Statistical Service Agency at http://www.armstat.am/en/ and is listed below. To describe the data used for constructing GDP, we use $Y : M$ to denote years with corresponding months, $Y = 2001, 2002, \ldots, 2008, 2009$, and $M = M1, M2, \ldots, M12$. We denote by $Y : Q$ years followed by the corresponding quarters $Q1, Q2, \ldots, Q4$.

The first measure of monthly real GDP, $RDGP_{Y:M}(1)$, for $2001 : M1 - 2008 : M12$, is constructed ignoring the official releases of quarterly real GDP, while the second measure of monthly real GDP, $RDGP_{Y:M}(2)$, is adjusted to reflect the official quarterly real GDP growth. The construction of $RDGP_{Y:M}(1)$ is detailed below.

- We start by readjusting the prices in 2009 to a common base date, rather than with respect to the previous month, since the latter are indicative of

Table 2.7: Available Data

Abbreviation	Description	Frequency
Nominal GDP (2009)		
$NGDP^1_{2009:M}$	nominal GDP industry (drams)	monthly
$NGDP^2_{2009:M}$	nominal GDP agriculture (drams)	monthly
$NGDP^3_{2009:M}$	nominal GDP construction (drams)	monthly
$NGDP^4_{2009:M}$	nominal GDP services (drams)	monthly
Production Price indexes (2009)		
$P^1_{2009:M}$	price index industry (% compared to previous period)	monthly
$P^2_{2009:M}$	price index agriculture (% compared to previous period)	monthly
$P^3_{2009:M}$	price index construction (% compared to previous period)	monthly
$P^4_{2009:M}$	price index services (% compared to previous period)	monthly
Real GDP (2001-2009)		
$RgGDP_{Y:M}$	real growth of total GDP (% compared to previous year)	monthly
$RGDPQ_{Y:Q}$	real GDP at constant 2005 average prices	quarterly
Rest of data (2001-2008)		
$CPI_{Y:M}$	consumer price index	monthly
$R_{Y:M}$	nominal interest rate on repurchase agreements	monthly
$e_{Y:M}$	real exchange rates	monthly

inflation rather than producer prices. The readjusted prices for each sector $j = 1, \ldots, 4$, $PM^j_{Y:M}$, are expressed with respect to the base 2008:M12, i.e.

$$PM^j_{2009:M} = \prod_{t=2009:M1}^{2009:M} P^j_t,$$

for $M = M2, \ldots, M12$. For example, if $Price^j_{Y:M}$ denotes the level of producer prices in $Y : M$, then, by definition,

$$PM^j_{2009:M2} = \frac{Price^j_{2009:M1}}{Price^j_{2008:M12}} \times \frac{Price^j_{2009:M2}}{Prices^j_{2009:M1}} = \frac{Price^j_{2009:M2}}{Price^j_{2008:M12}}.$$

- compute average 2009 monthly price indexes in each sector $j = 1, \ldots, 4$, with respect to base 2008:M12, as follows:

$$PA^j_{2009} = \frac{1}{12} \sum_{t=2009:M1}^{2009:M12} PM^j_t.$$

- We construct monthly price indexes in each sector $j = 1, \ldots, 4$, readjusted to the 2009 average prices rather than 2008:M12, as follows:

$$PS^j_{2009:M} = \frac{PM^j_{2009:M}}{PA^j_{2009}}.$$

Note that by division, the base 2008:M12 has been eliminated.

- Dividing monthly nominal GDP in each sector in 2009 by monthly prices indexes above (2009 average base) in each sector yields the monthly real GDP in each sector in 2009, $RGDP^j_{2009:M}$:

$$RDGP^j_{2009:M} = \frac{NGDP^j_{2009:M}}{PS^j_{2009:M}}.$$

- We add the real GDP in each sector in 2009 to obtain the monthly real GDP for the economy in 2009:

$$RGDP_{2009:M} = \sum_{j=1}^{4} RGDP^j_{2009:M}.$$

- From $RGDP_{2009:M}$ and the monthly cumulative real GDP growth rates with respect to the previous year from 2001:1-2009:12, $RgGDP_{Y:M}$, we can construct the real GDP in each month $RGDP_{Y:M}(1)$:

$$RGDP_{Y:M}(1) = \frac{RGDP_{2009:M}}{RgGDP_{2008:M} \times RgGDP_{2007:M} \times \ldots \times RgGDP_{Y+1:M}}.$$

  Here $Y : M = 2001 : M1 - 2008 : M12$.

This proxy is a sensible monthly GDP measure, but it ignores the official releases of quarterly real GDP, $RGDPQ_{Y:Q}$. We construct a second proxy that brings the first one closer to the published quarterly GDP, as follows:

- we first add the real GDP proxies $RGDP_{Y:M}(1)$ for each month of the quarter to obtain a measure of the quarterly GDP, e.g.

$$RGDPQ_{2008:Q1}(1) = RGDP_{2008:M1}(1) + RGDP_{2008:M2}(1) + RGDP_{2008:M3}(1).$$

- Note that $RGDPQ_{Y:Q}(1)$ is computed with respect to average 2009 prices, while the officially released real GDP is reported with respect to 2005 average prices. However, the growth rates of the officially released real GDP are by definition independent of prices. We first compute these growth rates, with respect to the previous quarter, say $RgGDP^*_{Y:Q}$, as:

$$RgGDP^*_{Y:Q} = \frac{RGDPQ_{Y:Q}}{RGDPQ_{Y:Q-1}}.$$

- Finally, we compute the second measure of real GDP, $RGDP_{Y:M}(2)$, with initial values the same as the first measure for $2001:M1 - 2001:M3$, and for the rest, using the growth rates $RgGDP^*_{Y:Q}$ forward. For example,

$$\begin{aligned} RGDP_{2001:M4}(2) &= RGDP_{2001:M4}(1) \times RgGDP^*_{2001:Q1} \\ RGDP_{2001:M5}(2) &= RGDP_{2001:M5}(1) \times RgGDP^*_{2001:Q1} \\ RGDP_{2001:M6}(2) &= RGDP_{2001:M6}(1) \times RgGDP^*_{2001:Q1}. \end{aligned}$$

Note that this last calculation appropriately uses quarterly growth rates rather than monthly growth rates, because then the first and the second measure of GDP appropriately differ by the official quarterly growth rates:

$$\begin{aligned} RGDPQ_{2001:Q2}(2) &= RGDP_{2001:M4}(2) + RGDP_{2001:M5}(2) + RGDP_{2001:M6}(2) \\ &= RgGDP^*_{2001:Q1} \left[\sum_{t=2001:M4}^{2001:M6} RGDP_t(1) \right] \\ &= RgGDP^*_{2001:Q1} \times RGDPQ_{2001:Q2}(1). \end{aligned}$$

To obtain the output gap y_t, we take logs, seasonally adjust the two measures of real GDP, and detrend the resulting measures using the usual Hodrick-Prescott (HP) filter with the program TRAMO/SEATS, and the default monthly constant 14400.[8]

Regarding the Consumer Price Index (CPI), data are disseminated by National Statistical Service Agency as a modified Laspeyres index with 2005 as a base year. The index is the weighted average monthly change in prices of 470 commodities. It is calculated for Yerevan and other 11 most densely populated regions. We seasonally adjust the log CPI in the same way as the log GDP, and compute our measure of inflation π_t as the difference of log CPI from previous month. We do not detrend the inflation rate for two reasons: first, as the plot indicates, its in-sample mean is approximately zero, and the inflation gaps will be approximately the same as

[8]Finding the optimal constant would be interesting, and we leave this to future research.

inflation; second, for checking effectiveness of inflation targeting, it is more useful to work with levels.

The Central Bank of Armenia main policy instruments is the repo (repurchase agreement) interest rate. The real interest rate is computed from the nominal interest rate, subtracting inflation $r_t = R_t - \pi_t$. Following Berg et al. (2006), we HP-detrend the nominal interest rate first, in the same way as log GDP.

Real exchange rates are official releases, in log nominal exchange rates in units of Armenian drams per US dollar, times the US dollar foreign price level per Armenian dram domestic price level. We HP-detrend the real exchange rates in the same way as log GDP. As usual in the literature, the real exchange rates and interest rates are not seasonally adjusted.

2.8 Appendix B: Figures

Figure 2.1: Monthly Armenian Data

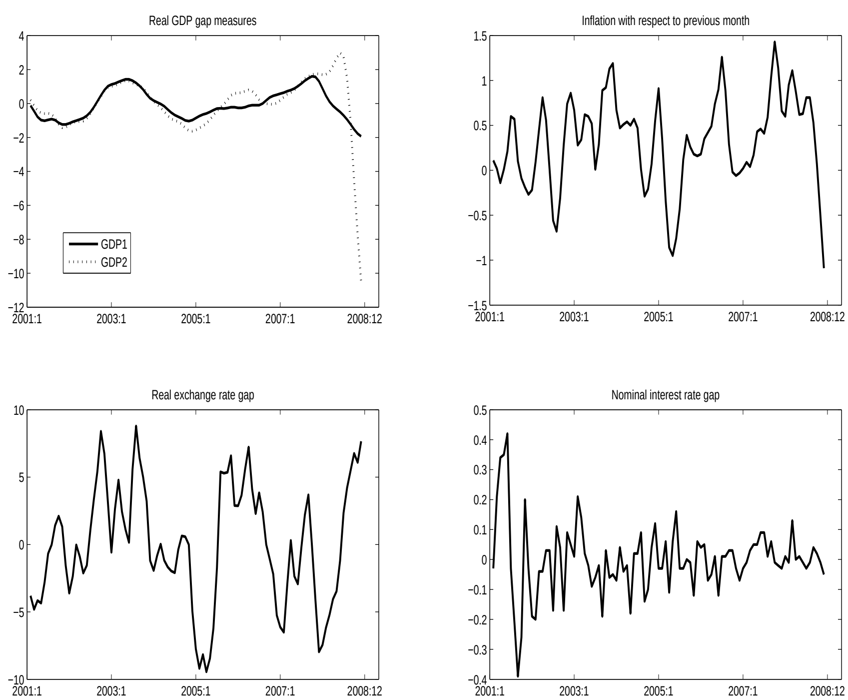


Figure 2.2: IRFs for an interest rate shock GMM 1

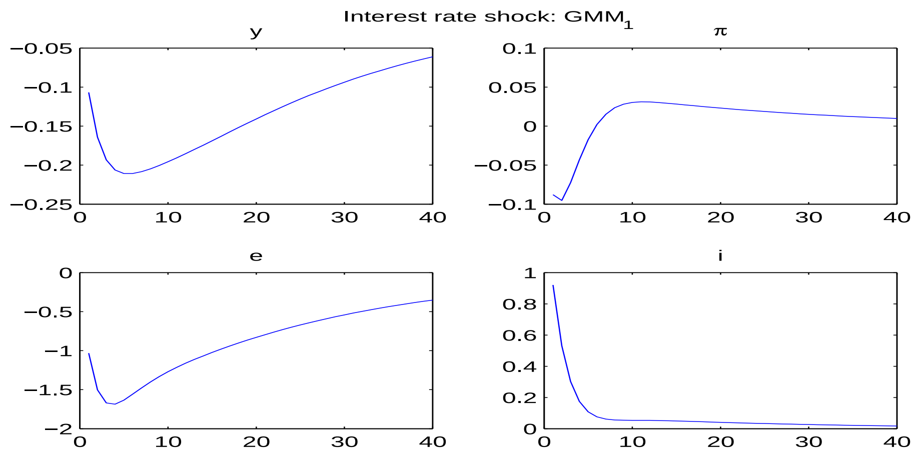


Figure 2.3: IRFs for an interest rate shock GMM 2

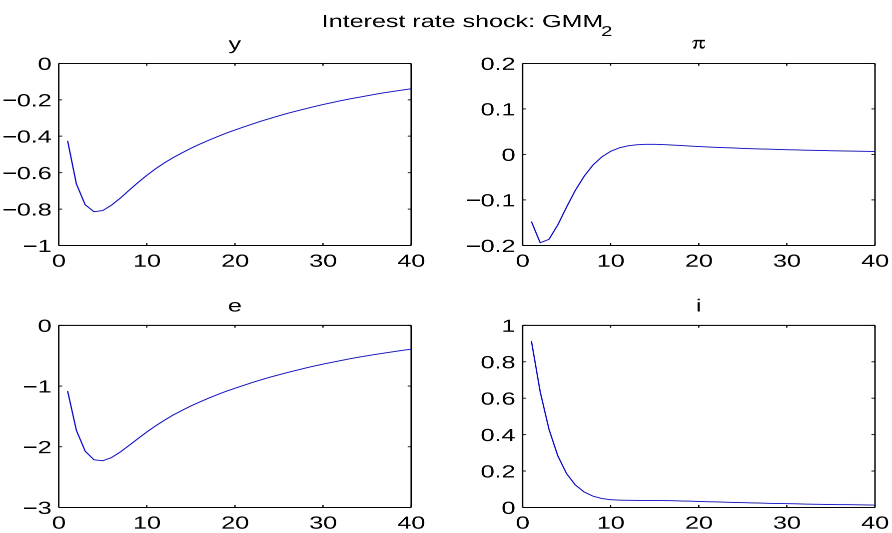


Figure 2.4: IRFs for an interest rate shock MDE 1

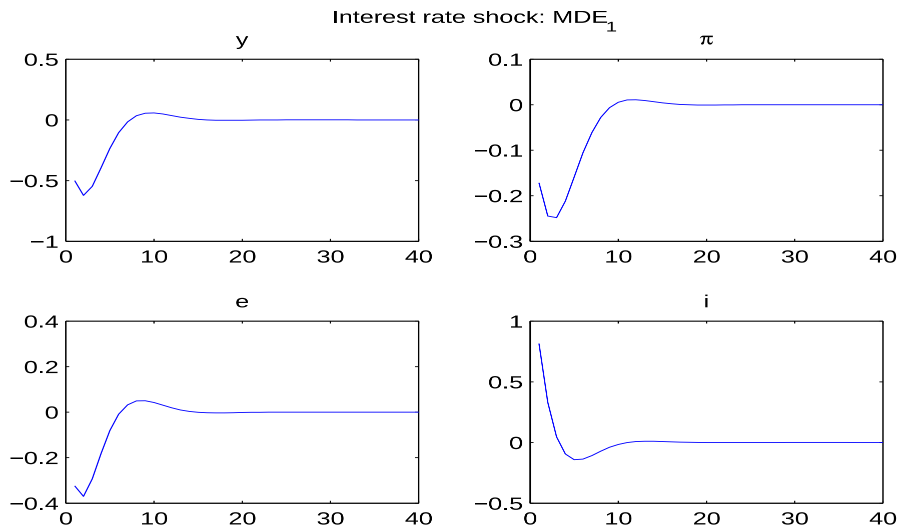


Figure 2.5: IRFs for an interest rate shock MDE 2

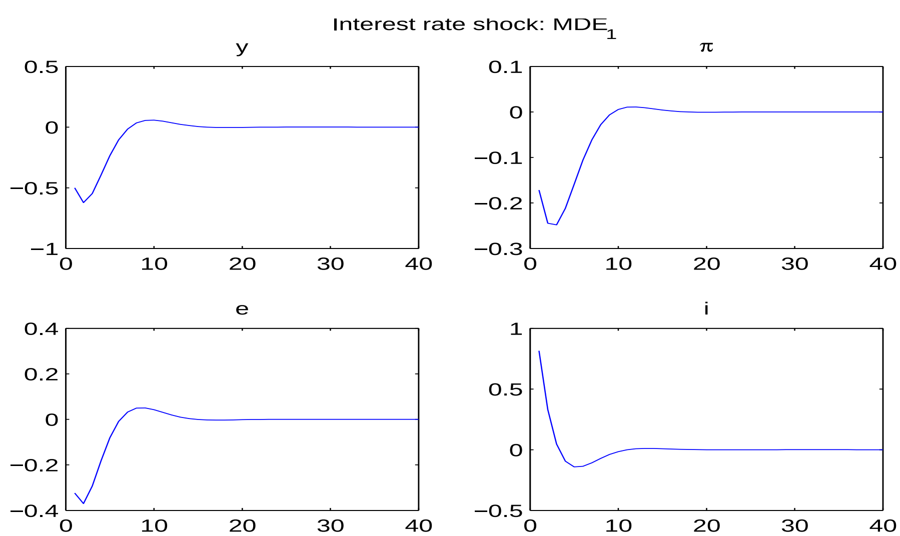


Figure 2.6: IRFs for an exchange rate shock GMM 1

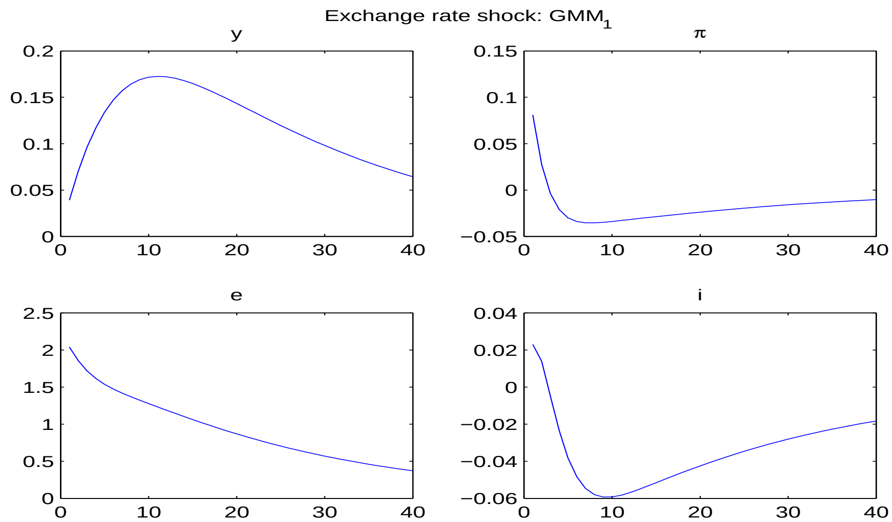


Figure 2.7: IRFs for an exchange rate shock GMM 2

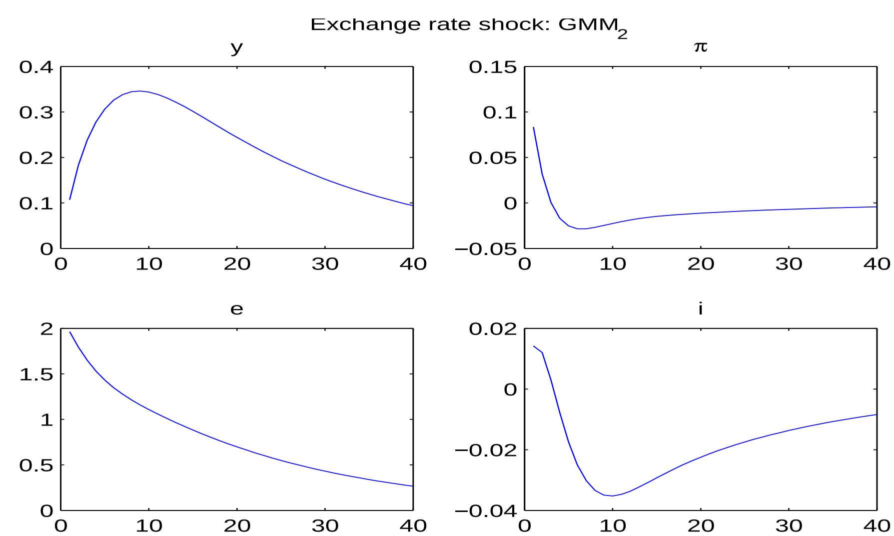


Figure 2.8: IRFs for an exchange rate shock MDE 1

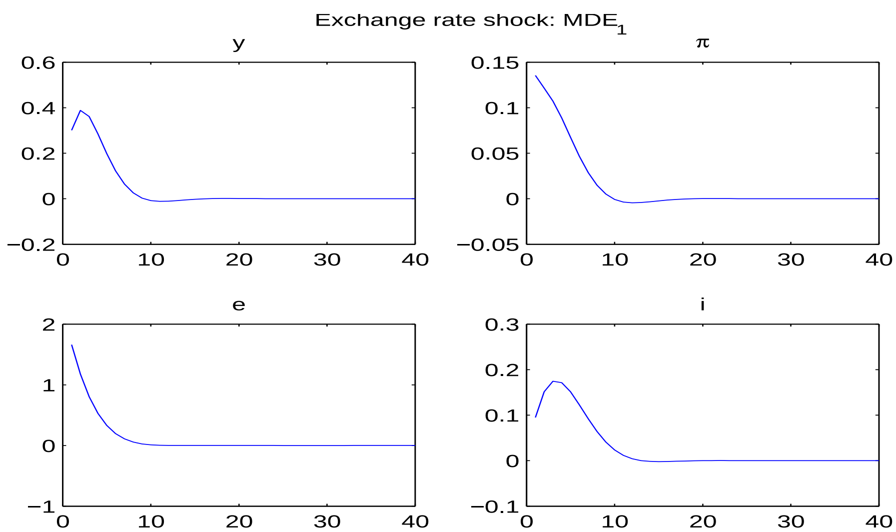
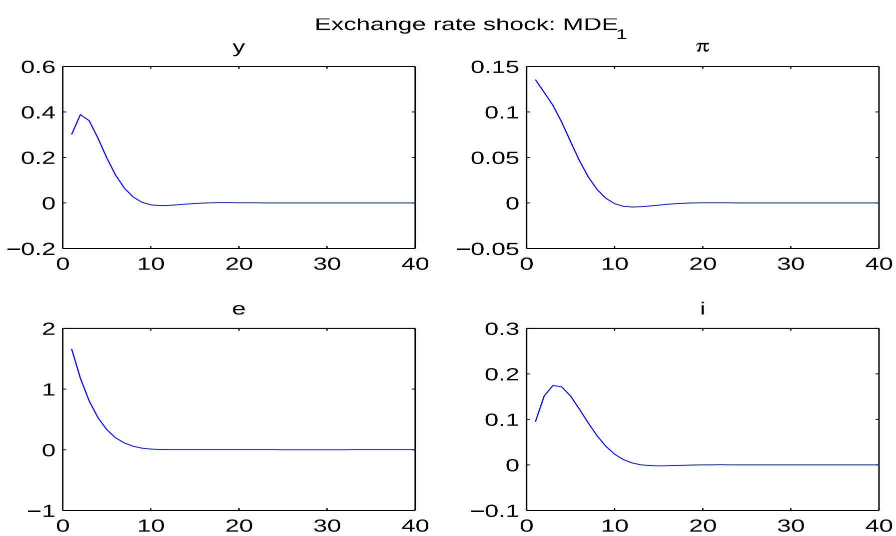


Figure 2.9: IRFs for an exchange rate shock MDE 2



Chapter 3

WALS estimation and forecasting in factor-based dynamic models with an application to Armenia

WALS estimation and forecasting in factor-based dynamic models with an application to Armenia*

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Abstract: Two model averaging approaches are used and compared in estimating and forecasting dynamic factor models, the well-known Bayesian model averaging (BMA) and the recently developed weighted average least squares (WALS). Both methods propose to combine frequentist estimators using Bayesian weights. We apply our framework to the Armenian economy using quarterly data from 2000–2010, and we estimate and forecast real GDP growth and inflation.

3.1 Introduction

In the recent macroeconomic literature, factor-based dynamic models have become popular. The idea underlying these models is that, while there are potentially a very large number of explanatory variables, most of the movement in the dependent variable can be explained by only a few variables or linear combinations thereof. One of the reasons why this happens is that the explanatory variables are often highly correlated.

We mention three recent examples where this approach has been successfully applied. Stock and Watson (2002) performed forecasting experiments for USA macroeconomic variables using 215 explanatory variables. From this

*We are grateful to the editor and two anonymous referees of the *International Econometric Review* for their constructive and helpful comments.

large number of variables they extracted a few factors to forecast key macroeconomic indicators. Forni et al. (2000, 2003) provided a time-series forecasting method based on spectral analysis, and applied this method to forecast Euro-area industrial production and inflation using 447 explanatory variables. Finally, Bernanke et al. (2005) took a vector autoregressive (VAR) model and augmented it with factors based on 120 macroeconomic variables. All these papers find that the mean squared errors of estimates and forecasts based on factor models are lower than those obtained from vector autoregressive models.

After extracting factors, these models are typically estimated in the traditional econometric way, that is, separating model selection and estimation. Recent advances in econometric theory allow us to combine model selection and estimation into one procedure, thus avoiding the undesirable problem of pretesting. This procedure is called 'Bayesian model averaging'. The purpose of the current paper is to apply the basic (non-dynamic) model averaging framework to dynamics and factor extraction, and to use this dynamic framework to explain and forecast Armenian real GDP growth and inflation.

In addition, we wish to compare in this context the standard Bayesian model averaging (BMA) approach to the 'weighted average least squares' (WALS) approach, recently developed in Magnus et al. (2010). The WALS approach has both theoretical and computational advantages over BMA. Theoretical, because it generates bounded risk and contains an explicit treatment of ignorance; computational, because its computing time increases linearly rather than exponentially with the dimension of the model selection space. In Magnus et al. (2010), WALS was applied to growth empirics, but without dynamics or lagged dependent variables.

Estimation and forecasting in factor-based dynamic models using the BMA algorithm was first applied by Koop and Potter (2004) to US data. Our current paper follows their general approach, but also reports on experiments where the two model averaging methods (WALS and BMA) are compared.

The paper is organized as follows. The factor-based dynamic model is introduced in Section 3.2. In Section 3.3 we present the WALS and BMA model averaging methods. Some characteristics of Armenia are provided in

Section 3.4, and the data are described in Section 3.5, which also contains a preliminary analysis of the data. The estimation results are given in Section 3.6. We report on two experiments. First, an estimation simulation in Section 3.7, then a forecast experiment in Section 3.8. Section 3.9 concludes.

3.2 The dynamic factor model

We consider the dynamic regression model

$$y_t = \alpha(L)y_{t-1} + \beta(L)x_{t-1} + \xi_t \qquad (t = 1, \ldots, T), \tag{3.1}$$

where y_t is a scalar dependent variable, x_t is a $k \times 1$ vector of nonrandom explanatory variables, $\alpha(L)$ and $\beta(L)$ are polynomials in the lag operator of dimensions p_1 and p_2, respectively, and ξ_t is a random vector of unobservable disturbances, independently and identically distributed as $\mathrm{N}(0, \sigma^2)$.

We have $p_1 + kp_2$ explanatory variables, which may be a large number. Moreover, many of the parameters may be close to zero. These two factors make it difficult to apply standard estimation methods (Koop and Potter, 2004). It is then common in the macro-econometric literature to replace the k explanatory variables with a much smaller number of variables. This can be achieved by using principal component or factor analysis algorithms. Then, after extracting the principal components, Model (3.1) can be rewritten as

$$y_t = \alpha(L)y_{t-1} + \gamma(L)f_{t-1} + \epsilon_t \qquad (t = 1, \ldots, T), \tag{3.2}$$

where f_t $(m \times 1)$ is the vector of extracted principal components and $\gamma(L)$ is a polynomial in the lag operator (Stock and Watson, 2002). We assume that $m < k$ and $m < T$. Of course, as noted by Koop and Potter (2004, p. 553), there is a cost in this type of transformation, namely that the interpretation of the variables is more difficult.

Koop and Potter (2004) were the first to show how Bayesian model averaging can be applied to estimation and forecasting using dynamic factor models. Their study applies BMA to the problem of forecasting GDP growth and inflation using quarterly US data on 162 time series. Our paper follows their approach, but also compares two competing estimation procedures: BMA and WALS. This will not only tell us something about the power of the two algorithms, but will also provide information about the robustness of our results.

3.3 Bayesian combinations of frequentist estimators

The idea behind combining estimators (or forecasts) is to use information from all models within a given family in a continuous fashion. In contrast to standard econometrics — where one first selects a model and then estimates the parameters within the chosen model, a discrete procedure — we combine the estimates from all models considered, where some models get a higher weight than others, based on priors and diagnostics. One advantage of this procedure is that we avoid the well-known pretest problem: our procedure is a joint procedure, where model selection and estimation are combined.

As our framework we choose the linear regression model

$$y = X_1\beta_1 + X_2\beta_2 + \epsilon = X\beta + \epsilon, \qquad \epsilon \sim \mathrm{N}(0, \sigma^2 I_n),$$

where y $(n \times 1)$ is the vector of observations, X_1 $(n \times k_1)$ and X_2 $(n \times k_2)$ are matrices of nonrandom regressors, ϵ is a random vector of unobservable disturbances, and β_1 and β_2 are unknown parameters which we need to estimate. We assume that $k_1 \geq 1$, $k_2 \geq 0$, $k = k_1 + k_2 \leq n - 1$, that $X = (X_1 : X_2)$ has full column-rank, and that the disturbances are independent and identically distributed.

The reason for distinguishing between X_1 and X_2 is that X_1 contains variables that we want to be in the model (whatever t-values or other diagnostics we find), while X_2 contains variables that may or may not be in the model. The columns of X_1 are called 'focus' regressors, the columns of X_2 'auxiliary' regressors. The uncertainty about each auxiliary regressor, that is whether we should or should not include the regressor in our model, is a very common situation, and the application of model averaging is then a natural procedure. Rather than choosing one model by preliminary diagnostic tests, we assume that each model tells us something of interest about our focus parameters. We do not, however, trust each model to the same degree, and the resulting weights are determined by priors and data. In this paper we concentrate on two model averaging algorithms, the well-known BMA algorithm and the recently introduced WALS algorithm. We briefly summarize each in turn. Full details and background references are provided in Magnus et al. (2010). The MATLAB codes can be obtained from www.janmagnus.nl/items/BMA.pdf, and the Stata codes are described in De Luca and Magnus (2011).

3.3.1 Bayesian model averaging (BMA)

With the exception of Magnus et al. (2010), the whole literature on Bayesian model averaging considers the case $k_1 = 1$. We summarize the approach of Magnus et al. (2010, Section 2). Since there are k_2 auxiliary regressors, we have 2^{k_2} different models to consider, because each auxiliary regressor can either be included or not. For each subset X_{2i} of $k_{2i} \leq k_2$ auxiliary variables we consider the regression

$$y = X_1\beta_1 + X_{2i}\beta_{2i} + \epsilon_i,$$

which we call model $\mathcal{M}_i$. If we let $p(\mathcal{M}_i)$ denote the prior probability that $\mathcal{M}_i$ is the true model, then the posterior probability for model $\mathcal{M}_i$ is given by

$$\lambda_i = p(\mathcal{M}_i|y) = \frac{p(\mathcal{M}_i)p(y|\mathcal{M}_i)}{\sum_j p(\mathcal{M}_j)p(y|\mathcal{M}_j)} \qquad (i = 1, \ldots, 2^{k_2}),$$

and if we take $p(\mathcal{M}_i) = 2^{-k_2}$, which is the common assumption, then $p(\mathcal{M}_i)$ does not depend on i, and we have simply $\lambda_i \propto p(y|\mathcal{M}_i)$, the marginal likelihood of y in model $\mathcal{M}_i$. If we adopt Zellner's g-prior, then

$$\lambda_i \propto \left(\frac{g_i}{1+g_i}\right)^{k_{2i}/2} (y'M_1A_iM_1y)^{-(n-k_1)/2},$$

where

$$A_i = \frac{g_i}{1+g_i} M_1 + \frac{1}{1+g_i} (M_1 - M_1 X_{2i} (X_{2i}' M_1 X_{2i})^{-1} X_{2i}' M_1)$$

and

$$M_1 = I_n - X_1 (X_1' X_1)^{-1} X_1'.$$

We specify g_i as

$$g_i = \frac{1}{\max(n, k_2^2)}.$$

The λ_i are the required weights to obtain the BMA estimates and precisions. For example, the BMA estimator of β_1 is given by

$$\mathrm{E}(\beta_1|y) = \sum_{i=1}^{2^{k_2}} \lambda_i \, \mathrm{E}(\beta_1|y, \mathcal{M}_i).$$

There are several problems with BMA. First, all 2^{k_2} models have to be evaluated implying a huge computational effort; second, the priors are based on the normal distribution, leading to unbounded risk; and third, the treatment of 'ignorance' is ad hoc and unsatisfactory. These problems are avoided in an alternative model averaging procedure, called WALS.

3.3.2 Weighted average least squares (WALS)

In the WALS algorithm, developed in Magnus et al. (2010, Section 3), we first 'orthogonalize' the columns of X_2 such that $P' X_2{}' M_1 X_2 P = \Lambda$, where P is orthogonal and Λ is diagonal. Then we define $X_2^* = X_2 P \Lambda^{-1/2}$ and $\beta_2^* = \Lambda^{1/2} P' \beta_2$, so that $X_2^* \beta_2^* = X_2 \beta_2$. Our prior will be on β_1 and β_2^* (rather than on β_2), and this gives us enormous computational advantage, because all models which include x_{2j}^* as a regressor will have the same estimator of β_{2j}^*, irrespective which other β_2^*'s are estimated.

The second ingredient is the 'equivalence theorem' (Magnus and Durbin, 1999; Danilov and Magnus, 2004), which tells us that the WALS estimator b_1 of β_1 will be 'good' (in the mean squared error sense) if and only if $W \hat{\beta}_2^*$ is a good estimator of β_2^*, where $\hat{\beta}_2^*$ denotes the least squares estimator of β_2^* in the unrestricted model, and W is a random diagonal matrix of order $k_2 \times k_2$. The diagonal elements w_j of W will depend on the weights λ_i, but while there are 2^{k_2} λ's, there are only k_2 w's. This is where the computational advantage comes from.

The third ingredient is the treatment of ignorance. Based on the fact that a t-value of one indicates that including an auxiliary regressor gives us the same mean squared error of the estimated focus parameter as excluding the auxiliary regressor, we define ignorance on an auxiliary parameter η by the properties

$$\Pr(\eta > 0) = \Pr(\eta < 0), \qquad \Pr(|\eta| > 1) = \Pr(|\eta| < 1),$$

and we propose the Laplace distribution

$$\pi(\eta) = (c/2)\exp(-c|\eta|)$$

with $c = \log 2$.

The WALS estimator is a Bayesian combination of frequentist estimators, and possesses major advantages over standard Bayesian model averaging (BMA) estimators: the WALS estimator has bounded risk, allows a coherent treatment of ignorance, and its computational effort is negligible. The sampling properties of the WALS estimator as compared to BMA estimators have been examined in Magnus et al. (2011), where Monte Carlo evidence shows that the WALS estimator performs better than standard BMA and pretest alternatives. Because of the light computational cost, extensions are possible in many directions. For example, Magnus et al. (2011) extend the WALS theory to allow for nonspherical disturbances.

In the current paper we consider a broader class of linear models than before, by allowing the regressors to include lagged dependent variables. The y_t will then be correlated with the current and all previous disturbances, but uncorrelated with all future disturbances. Hence, the regressor y_{t-1} will be uncorrelated with the current disturbance and all future disturbances, although it will be correlated with all previous disturbances. The standard ordinary least squares (OLS) assumptions do therefore not hold, and the finite-sample properties of the least squares estimators are not valid. However, as shown by Mann and Wald (1943), these properties will hold asymptotically.

We need to determine which variables are focus and which are auxiliary. The focus variables are those which we want in the model on theoretical or other grounds, irrespective of any diagnostics. The choice is not always easy and often subjective. It is guided by economic-theoretical considerations and by previous empirical experience. But it is also guided by the purpose of the model: if our primary purpose is to study the effect of x and z on y, then it would seem ill-advised to remove x or z from the model; these are necessarily focus variables.

In our setting, we shall assume that the lagged dependent variables are always focus regressors. But the extracted principal components can be either focus or auxiliary. Thus we write

$$y = X_1\beta_1 + X_2\beta_2 + \epsilon, \tag{3.3}$$

where X_1 contains the lagged dependent variables and a subset (possibly empty) of the principal components, and X_2 contains the remainder of the principal components. In this form we can apply BMA and WALS to this system.

3.4 Characteristics of Armenia

Armenia is a small country in the Southern Caucasus, slightly larger than Wales, slightly smaller than Belgium, and about 65% the size of Moscow region. Most of its territory (80%) consists of mountains. It is bordered by Georgia to the North and East, Azerbaijan to the West, and Turkey and Iran to the South. Armenia was the first nation to adopt Christianity as a state religion, in 301 AD. The population of Armenia, close to three million people, is homogeneous: about 98% is ethnic Armenian with some small minorities, mostly Yazidis (1.3%) and Russians (0.5%).

Until 1991 Armenia was a republic of the former Soviet Union. During the Soviet period Armenia was transformed from an agricultural to an industrial society, and produced machine tools, electronic products, synthetic rubber, and textiles to trade with other Soviet republics in exchange for raw materials and energy. But the regional conflict with Azerbaijan over Nagorno-Karabakh and the break-up of the Soviet Union contributed to a severe economic decline in the early 1990s. As a result, GDP in 1992/93 was only about 40% of the level in 1989.

In 1994 the Armenian Government launched an ambitious IMF-sponsored economic program, which has resulted in positive growth since 1995. Today, Armenia's economy is stable with a high growth rate and low inflation. From 2000–2009 the economy grew at an annual average rate of 8.8%, while the inflation rate was 3.0%. The reason for this rapid growth lies mainly in the expanding construction and service sectors; according to Armenia's National Statistical Agency, the construction sector accounted for about 27% of GDP in 2008. Cash remittances from migrant workers (of which 95% are employed in Russia) are another important factor.

Despite marked progress, Armenia still suffers from a large trade imbalance which is an impediment to economic growth. Armenia is largely dependent upon foreign aid and remittances from Armenian nationals working abroad. The total value of foreign debt is high: the ratio between foreign debt and GDP has reached 46%. The unemployment rate is nearly 30%, and a huge gap exists between actual and potential GDP.

3.5 Data description and preliminary analysis

Our data consist of quarterly time series of 42 macroeconomic variables from 2000 (second quarter) to 2010 (fourth quarter), in total 43 observations for each variable. This set comprises information on national accounts data (9 variables) and consumer prices and exchange rate data (13 variables), listed in Table 3.1; and on financial and monetary policy indicators (13 variables) and international macroeconomic indicators (7 variables), listed in Table 3.2. A full description of the data is presented in the appendix.

All variables in Table 3.1 are in logarithmic form, in first differences. The variables in column 1 are all real. The variables in columns 1 and 2 are

Table 3.1: National accounts, consumer prices, and exchange rates

National accounts	Price indices	Price indices and exchange rates
GDP	Consumer price index	Wheat price index
Consumption	Food price index	Fuel price index
Investment	Nonfood price index	Imported food price index
Exports	Services price index	Imported nonfood price index
Imports	Home food price index	Administrative price index
Industrial output		AMD/USD exchange rate
Agricultural output		AMD/EURO exchange rate
Construction		AMD/RR exchange rate
Services		

Table 3.2: Financial, monetary, and international indicators

Financial policy indicators	Interest rates	International indicators
Cash money	AMD deposits	USA real GDP
Money aggregate, M0	USD deposits	EU real GDP
Money aggregate, M1	AMD loans	USA consumer price index
Money aggregate, M2X	USD loans	EU consumer price index
Total deposits	Central Bank interbank	Gasoline price index
Loans to economy		Petroleum price index
Loans to enterprizes		Wheat price index
Loans to households		

seasonally adjusted. The variables in Table 3.2, columns 1 and 3, are also in logarithmic form, in first differences, and seasonally adjusted. The interest rates (column 2) are not in logarithmic form, not in first differences, and not seasonally adjusted. The international indicators in column 3 are taken from the International Financial Statistics (IFS) published by the IMF and are already seasonally adjusted.

The dependent variables are either 'growth', denoted G, defined as the quarterly growth rate of real GDP, and 'inflation', denoted INF, defined as the quarterly growth rate of the consumer price index CPI. The dynamics of the observed quarterly real GDP data are presented in Figures 3.1 (real GDP) and 3.2 (growth), and the dynamics of the observed quarterly CPI data in Figures 3.3 (CPI) and 3.4 (inflation). We see from Figures 3.1–3.2 that the 2008 global economic crisis led to a sharp decrease in real GDP in

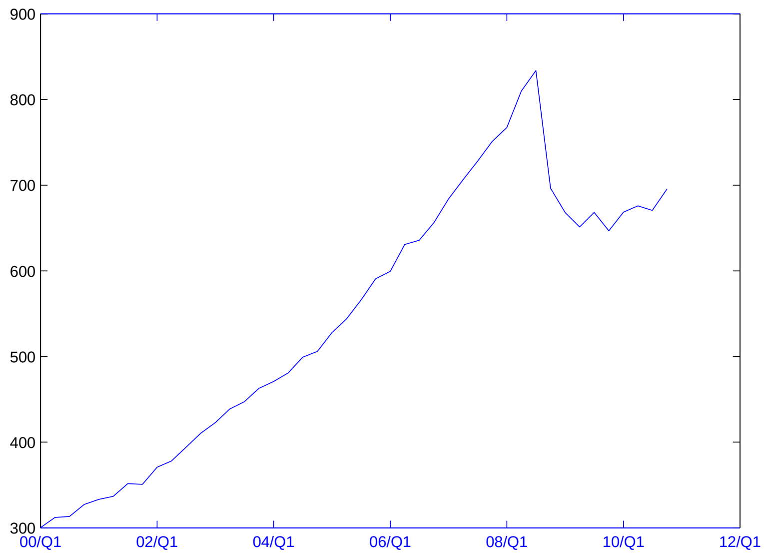

Figure 3.1: Seasonally adjusted real GDP, 2000/Q1–2010/Q4 (billion Armenian drams)

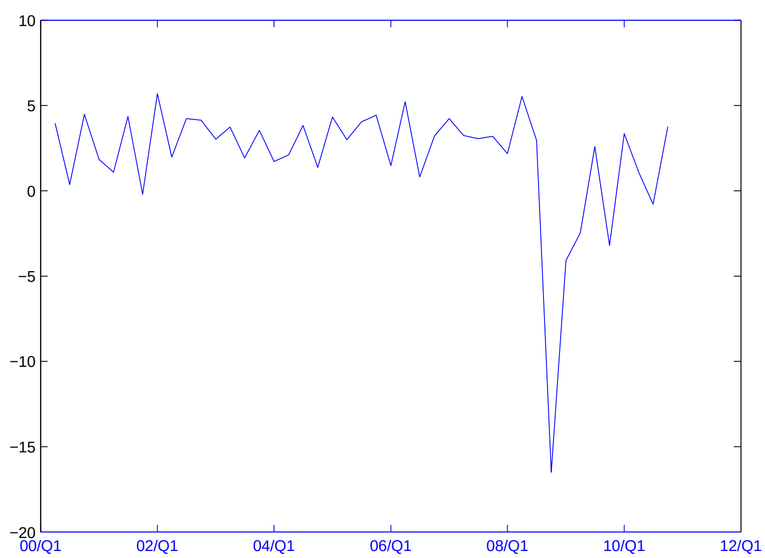

Figure 3.2: Quarterly growth rate of real GDP, 2000/Q2–2010/Q4

the 4-th quarter of 2008. Real GDP declined by about 15% in 2009 compared

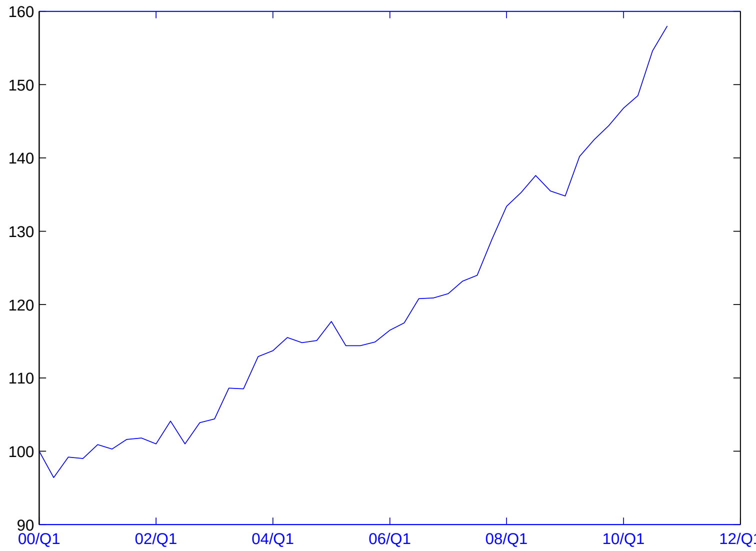

Figure 3.3: Seasonally adjusted CPI, 2000/Q1–2010/Q4 (2000/Q1 = 100)

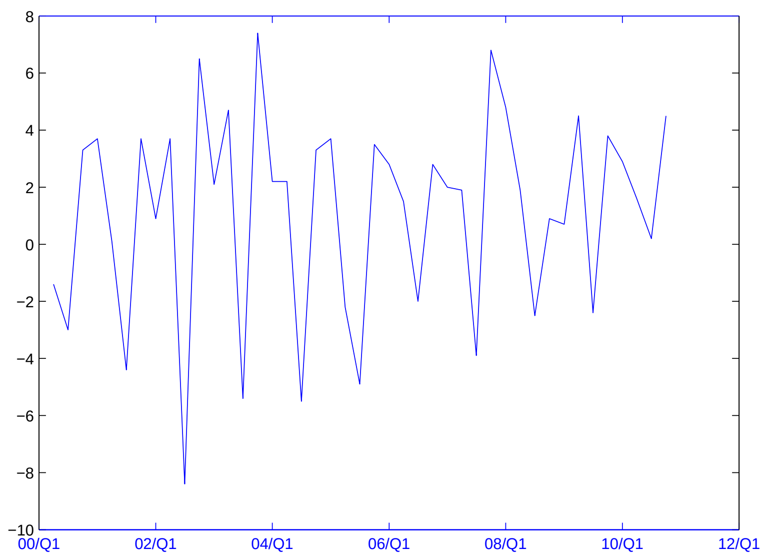

Figure 3.4: Inflation (quarterly growth rate of CPI), 2000/Q2–2010/Q4

to 2008, primarily because the remittance and private capital flow boom came to an end, leading to the collapse of the construction sector. Since 2010 the growth of real GDP is again positive. Figures 3.3–3.4 show that inflation has responded less dramatically during the global crisis; it remained low at about 3.5% in 2009, due to weak domestic demand and low import prices. From Figures 3.2 and 3.4 we also conclude that the quarterly growth rate of real GDP and inflation are both stationary.

Table 3.3: Correlations ρ between initial variables and ten extracted factors, $|\rho| \geq 0.70$

	1	2	3	4	5	6	7	8	9	10
Inv			0.78							
Exp							0.70			
Imp							0.74			
Ind							0.81			
Agr									0.71	
$Cstr$			0.71							
$Serv$								0.73		
$NFood_{pr}$		0.84								
$Wheat_{pr}$						0.75				
$Fuel_{pr}$		0.83								
$NFood_{pr}^{imp}$		0.72								
$HFood_{pr}$										0.78
Exr_{usd}^{amd}		0.73								
Exr_{euro}^{amd}		0.76								
Exr_{rr}^{amd}		0.80								
$Cash$				0.83						
$M0$				0.72						
Dep					0.80					
$Cred$					0.74					
$Cred_{firm}$					0.82					
Dep_{ir}^{d}	0.93									
Dep_{ir}^{f}	0.95									
$Cred_{ir}^{d}$	0.90									
$Cred_{ir}^{f}$	0.76									
CB_{inter}	0.89									
GDP_{eu}^{def}									0.77	

In this paper we estimate and forecast factor-based dynamic models using principal components. These principal components are based on the underlying data set of 40 variables (excluding dependent variables, that is real GDP growth and inflation). The extracted principal components have been given names, based on the correlation coefficients between the extracted principal components and the underlying time series. In Table 3.3 we present the correlations ρ between the initial variables and the ten extracted factors for $|\rho| \geq 0.70$. We name the extracted factors according to the highest correlation coefficients. The first factor is highly correlated with the interest rate time series, in particular with Dep_{ir}^{d}, Dep_{ir}^{f}, $Cred_{ir}^{d}$, $Cred_{ir}^{f}$, and CB_{inter}. Therefore this factor is interpreted as the interest rate factor (*Int_rate*). The second factor is highly correlated with $NFood_{pr}$, $Fuel_{pr}$, $NFood_{pr}^{imp}$, Exr_{usd}^{amd}, Exr_{euro}^{amd}, and Exr_{rr}^{amd}. Since fuel prices and imported goods price indexes ($Fuel_{pr}$ and $NFood_{pr}^{imp}$) are dependent on the exchange rate dynamics, we call this factor 'exchange rate' (*Ex_rate*). Factor 3 is highly correlated with the gross investment (*Inv*) and construction (*Cstr*), so we call it 'investment' (*Invest*). Factor 4 is highly correlated with monetary aggregates, particularly with cash money in circulation (*Cash*) and monetary base (*M0*). Therefore this factor is called 'monetary aggregate' (*Mon_agg*). Factor 5 is highly correlated with deposits and credits to the economy, so we name it 'credit' (*Credit*). Factor 6 is highly correlated with the price indexes, particularly with food price indexes (especially wheat price indexes), so we call this factor 'price index' (*Pr_index*). Factor 7 is mainly correlated with the open economy indices, such as import and export dynamics, therefore this factor can be called 'import or export' (*ImpExp*). Factor 8 is highly correlated with services dynamics, which is one of the main branches of the economy and its dynamics have an important impact on current GDP dynamics. Therefore we call this factor 'national accounts' (*Nat_acc*). Factor 9 is mainly correlated with the international GDP variables, which is why we call this factor 'international GDP' (*Gstar*). Finally, factor 10 is highly correlated with home price index dynamics and so we call it 'home price index' (*Hfood_pr*).

Some important characteristics of the extracted principal components are presented in the Table 3.4. The first principal component is *Int_rate* and its contribution to the total variance of the underlying variables is 12.78%. The

Table 3.4: Characteristics of the extracted principal components

Principal components	Rotated eigenvalue	% of total variance	Cumulative %	Correlation with growth	Correlation with inflation
Int_rate	5.11	12.78	12.78	0.04	−0.21
Ex_rate	5.00	12.51	25.29	−0.03	0.28
Invest	3.90	9.74	35.03	0.65	0.07
Mon_agg	3.60	9.00	44.03	0.43	0.01
Credit	3.19	7.98	52.01	0.02	0.10
Pr_index	2.62	6.54	58.55	0.23	0.62
ImpExp	2.58	6.46	65.01	0.22	−0.03
Nat_acc	2.37	5.93	70.93	0.31	−0.27
Gstar	2.01	5.01	75.95	0.29	−0.12
Hfood_pr	1.69	4.23	80.18	0.09	0.47

second principal component is *Ex_rate* with a contribution of 12.51%, and the third is *Invest* with a contribution of 9.74%. The ten most important principal components (those with a rotated eigenvalue larger than 1) explain more than 80% of the variance of the underlying variables, which we consider to be sufficient.

Table 3.5: Focus and auxiliary variables ($j = 1, \dots, 4$)

Growth G			Inflation INF		
Regressor	Model 1.1	Model 1.2	Regressor	Model 2.1	Model 2.2
Intercept	focus	focus	*Intercept*	focus	focus
G_{t-j}	focus	focus	INF_{t-j}	focus	focus
$Invest_{t-j}$	auxiliary	focus	Ex_rate_{t-j}	auxiliary	focus
$ImpExp_{t-j}$	auxiliary	focus	Pr_index_{t-j}	auxiliary	focus
Nat_acc_{t-j}	auxiliary	focus	$Hfood\_pr_{t-j}$	auxiliary	focus
Mon_agg_{t-j}	auxiliary	auxiliary	Int_rate_{t-j}	auxiliary	auxiliary
Pr_index_{t-j}	auxiliary	auxiliary	$Credit_{t-j}$	auxiliary	auxiliary
$Gstar_{t-j}$	auxiliary	auxiliary	Nat_acc_{t-j}	auxiliary	auxiliary
			$Gstar_{t-j}$	auxiliary	auxiliary

Each of the extracted principal components could be used for estimation in our factor-based dynamic models. However, we use our knowledge of economic theory and Armenian practice to include only those principal components which contain important information about real GDP growth and inflation. Regarding real GDP growth, the highest correlations are obtained by *Invest*, *Mon_agg*, *Pr_index*, *ImpExp*, *Nat_acc*, and *Gstar*. Regarding inflation, the highest correlations are obtained by *Int_rate*, *Ex_rate*, *Credit*, *Pr_index*, *Nat_acc*, *Gstar*, and *Hfood_pr*.

These choices then lead to the four models in Table 3.5. Model 1 refers to GDP growth and Model 2 to inflation. Each model has two variants. In variant 1 (Models 1.1 and 2.1) we take as our focus variables only the lagged values of the dependent variable (and the intercept), while all other variables are auxiliary, that is, we are uncertain whether they should be in the model or not. This is the same type of specification as in Koop and Potter (2004). In variant 2 (Models 1.2 and 2.2) we have more focus variables. Here we argue that some of the extracted principal components must always be in the model so that they should be treated as focus variables. For Model 1.2 this applies to *Invest*, *ImpExp*, and *Nat_acc*, because the level of real GDP growth depends directly on the level of these components. For Model 2.2 it applies to *Ex_rate*, *Pr_index*, and *Hfood_pr*, because these principal components are known to have a direct impact on the rate of inflation. Having thus specified the four models, we now turn to their estimation and forecasting using the WALS and BMA algorithms.

3.6 Estimation results

We have two models, one for GDP growth and one for inflation. Each model has two variants, one with only the intercept and the lagged dependent variable as focus regressors, the other with additional focus regressors. For each of the four cases we consider one lag, two lags, three lags, or four lags. We do not use more than four lags, because, in practice, factor-based dynamic models (DFM) are mainly used for short-term forecasting, while for long-term forecasts practitioners typically use dynamic stochastic general equilibrium

(DSGE) models. This is also true at the Central bank of Armenia: for short-term forecasts (up to four quarters) DFM and Bayesian VAR models are used, while DSGE models are used for long-term forecasts (two or more years). Since we work with quarterly data, four lags means one year, so that the lagged period (four quarters) equals the maximum predicted period. Of course, there is also considerable local experience with short-term forecasting, indicating that four lags provide a reasonable lag structure.

In addition, we have two different model averaging algorithms: WALS and BMA. All WALS and BMA results are obtained using MATLAB codes, which are freely available from www.janmagnus.nl/items/BMA.pdf. The WALS estimates for the GDP growth equation are presented in Tables 3.6 and 3.7.

In Table 3.6 the focus variables are the intercept and lagged values of real GDP growth, while in Table 3.7 we add lagged values of *Invest*, *ImpExp* and *Nat_acc* to the focus variables. The first lag G_{t-1} of real GDP growth is positively correlated with current GDP growth G_t, and the parameter appears to be close to one in both models, and in each of the four lag structures, showing a certain amount of robustness. Current GDP growth is negatively correlated with lagged values of *Invest*, and positively correlated with *Nat_acc*. This is to be expected, since one of the main ingredients of *Nat_acc* is final consumption, which in turn is one of the basic components of GDP. Thus, final consumption should be positively correlated with GDP. Also, current consumption is positively correlated with consumption in the previous period, and hence consumption of the previous period and GDP of the current period should be positively correlated. The *Mon_agg* component is also positively correlated with current real GDP growth, which tells us that monetary aggregates can be considered as potential leading indicators for changes in the dynamics of real GDP.

Concerning *Invest* we see that the first lag is negatively correlated with current GDP growth, but that higher lags are positively correlated. Apparently, investments have a short-term (one quarter) negative impact, but a medium-term (2–4 quarters) positive impact on economic activity (and therefore on

Table 3.6: WALS estimates for Model 1 (Growth), Version 1

	One lag	Two lags	Three lags	Four lags
Focus regressors				
Intercept	0.43 (0.52)	1.05 (0.78)	2.51 (1.43)	1.02 (1.90)
G_{t-1}	0.77 (0.24)	0.97 (0.31)	0.92 (0.45)	0.78 (0.57)
G_{t-2}	—	−0.52 (0.25)	−1.11 (0.41)	−1.05 (0.61)
G_{t-3}	—	—	−0.13 (0.29)	0.51 (0.72)
G_{t-4}	—	—	—	0.20 (0.48)
Auxiliary regressors				
$Invest_{t-1}$	−0.25 (0.41)	−0.49 (0.47)	−0.49 (0.61)	−0.35 (0.73)
$ImpExp_{t-1}$	−0.14 (0.25)	−0.08 (0.23)	−0.01 (0.26)	0.12 (0.37)
Nat_acc_{t-1}	0.37 (0.27)	0.19 (0.29)	0.37 (0.36)	0.67 (0.62)
Mon_agg_{t-1}	0.14 (0.31)	0.29 (0.32)	0.19 (0.39)	0.48 (0.54)
Pr_index_{t-1}	0.10 (0.23)	0.17 (0.29)	0.08 (0.36)	0.19 (0.37)
$Gstar_{t-1}$	−0.22 (0.27)	0.03 (0.32)	−0.29 (0.38)	0.00 (0.63)
$Invest_{t-2}$	—	0.18 (0.45)	0.99 (0.69)	0.43 (0.69)
$ImpExp_{t-2}$	—	0.24 (0.23)	0.35 (0.26)	0.26 (0.44)
Nat_acc_{t-2}	—	0.68 (0.28)	0.92 (0.34)	0.79 (0.52)
Mon_agg_{t-2}	—	0.26 (0.31)	0.72 (0.42)	0.87 (0.88)
Pr_index_{t-2}	—	−0.05 (0.28)	0.71 (0.39)	0.27 (0.38)
$Gstar_{t-2}$	—	−0.01 (0.26)	0.80 (0.40)	0.89 (0.59)
$Invest_{t-3}$	—	—	0.57 (0.46)	−0.79 (1.36)
$ImpExp_{t-3}$	—	—	0.41 (0.24)	0.29 (0.38)
Nat_acc_{t-3}	—	—	0.47 (0.34)	0.09 (0.52)
Mon_agg_{t-3}	—	—	0.65 (0.38)	0.35 (0.59)
Pr_index_{t-3}	—	—	−0.22 (0.29)	−0.61 (0.56)
$Gstar_{t-3}$	—	—	−0.22 (0.29)	−0.76 (0.91)
$Invest_{t-4}$	—	—	—	−0.75(0.78)
$ImpExp_{t-4}$	—	—	—	−0.07 (0.26)
Nat_acc_{t-4}	—	—	—	0.11 (0.61)
Mon_agg_{t-4}	—	—	—	−0.67 (0.42)
Pr_index_{t-4}	—	—	—	−0.14 (0.63)
$Gstar_{t-4}$	—	—	—	−0.11 (0.51)

Note: Numbers in brackets are standard errors in the posterior distribution.
The dimension of the dependent variable decreases from 42 (one lag) to 39 (four lags).

the growth level). Many of the auxiliary parameters are not statistically significant.

In Tables 3.8 and 3.9 we report the corresponding results for inflation. Lagged values of inflation are positively correlated with current inflation, but

Table 3.7: WALS estimates for Model 1 (Growth), Version 2

	One lag	Two lags	Three lags	Four lags
Focus regressors				
Intercept	0.37 (0.54)	0.98 (0.83)	2.56 (1.40)	1.18 (1.94)
G_{t-1}	0.80 (0.25)	1.08 (0.33)	1.08 (0.45)	0.85 (0.58)
$Invest_{t-1}$	−0.40 (0.46)	−0.85 (0.52)	−0.89 (0.61)	−0.62 (0.76)
$ImpExp_{t-1}$	−0.21 (0.28)	−0.12 (0.25)	−0.02 (0.27)	0.06 (0.41)
Nat_acc_{t-1}	0.54 (0.30)	0.18 (0.32)	0.28 (0.37)	0.58 (0.64)
G_{t-2}	—	−0.60 (0.26)	−1.29 (0.43)	−1.15 (0.64)
$Invest_{t-2}$	—	0.20 (0.48)	1.17 (0.71)	0.45 (0.74)
$ImpExp_{t-2}$	—	0.29 (0.26)	0.42 (0.28)	0.28 (0.46)
Nat_acc_{t-2}	—	0.94 (0.31)	1.18 (0.36)	1.01 (0.54)
G_{t-3}	—	—	−0.14 (0.30)	0.51 (0.74)
$Invest_{t-3}$	—	—	0.74 (0.48)	−0.71 (1.38)
$ImpExp_{t-3}$	—	—	0.49 (0.26)	0.31 (0.40)
Nat_acc_{t-3}	—	—	0.55 (0.37)	0.14 (0.56)
G_{t-4}	—	—	—	0.15 (0.52)
$Invest_{t-4}$	—	—	—	−0.57 (0.83)
$ImpExp_{t-4}$	—	—	—	0.00 (0.29)
Nat_acc_{t-4}	—	—	—	0.18 (0.65)
Auxiliary regressors				
Mon_agg_{t-1}	0.13 (0.31)	0.26 (0.31)	0.11 (0.38)	0.48 (0.53)
Pr_index_{t-1}	0.08 (0.23)	0.16 (0.27)	0.06 (0.34)	0.19 (0.37)
$Gstar_{t-1}$	−0.20 (0.26)	0.04 (0.31)	−0.28 (0.38)	−0.06 (0.62)
Mon_agg_{t-2}	—	0.25 (0.30)	0.72 (0.41)	0.92 (0.89)
Pr_index_{t-2}	—	−0.03 (0.25)	0.73 (0.39)	0.28 (0.39)
$Gstar_{t-2}$	—	0.01 (0.25)	0.80 (0.41)	0.93 (0.59)
Mon_agg_{t-3}	—	—	0.63 (0.38)	0.36 (0.58)
Pr_index_{t-3}	—	—	−0.18 (0.28)	−0.55 (0.56)
$Gstar_{t-3}$	—	—	−0.20 (0.28)	−0.79 (0.91)
Mon_agg_{t-4}	—	—	—	−0.67 (0.44)
Pr_index_{t-4}	—	—	—	−0.14 (0.65)
$Gstar_{t-4}$	—	—	—	−0.24 (0.54)

Note: Numbers in brackets are standard errors in the posterior distribution.
The dimension of the dependent variable decreases from 42 (one lag) to 39 (four lags).

comparing with the growth estimates we find that inflation in Armenia is less backward-looking than growth. The first lags of *Pr_index* and *Ex_rate* are positively correlated with current inflation, which is again reasonable. The positive correlation between *Pr_index* and inflation tells us that price

Table 3.8: WALS estimates for Model 2 (Inflation), Version 1

	One lag	Two lags	Three lags	Four lags
Focus regressors				
Intercept	0.87 (0.33)	0.16 (0.59)	0.32 (0.88)	−0.54 (1.88)
INF_{t-1}	0.27 (0.27)	0.66 (0.37)	0.35 (0.69)	0.69 (1.41)
INF_{t-2}	—	0.20 (0.30)	0.38 (0.58)	0.72 (1.16)
INF_{t-3}	—	—	−0.01 (0.44)	−0.56 (0.82)
INF_{t-4}	—	—	—	0.62 (0.74)
Auxiliary regressors				
Ex_rate_{t-1}	0.13 (0.13)	−0.02 (0.18)	0.07 (0.26)	−0.07 (0.42)
Pr_index_{t-1}	0.31 (0.21)	0.14 (0.25)	0.33 (0.43)	0.27 (0.81)
$Hfood\_pr_{t-1}$	0.01 (0.19)	−0.29 (0.26)	−0.14 (0.40)	−0.47 (0.83)
Int_rate_{t-1}	−0.06 (0.12)	0.28 (0.45)	0.20 (0.70)	0.60 (0.93)
$Credit_{t-1}$	0.09 (0.11)	−0.24 (0.22)	−0.19 (0.38)	−0.02 (0.53)
Nat_acc_{t-1}	−0.03 (0.13)	0.11 (0.19)	0.07 (0.27)	0.12 (0.37)
$Gstar_{t-1}$	−0.17 (0.12)	0.03 (0.19)	0.04 (0.34)	0.21 (0.55)
Ex_rate_{t-2}	—	−0.01 (0.16)	−0.06 (0.30)	0.08 (0.50)
Pr_index_{t-2}	—	−0.24 (0.26)	−0.20 (0.34)	−0.52 (0.62)
$Hfood\_pr_{t-2}$	—	−0.15 (0.22)	−0.26 (0.44)	−0.57 (0.83)
Int_rate_{t-2}	—	−0.31 (0.43)	0.09 (0.76)	−0.59 (1.35)
$Credit_{t-2}$	—	0.28 (0.20)	0.00 (0.46)	0.11 (0.93)
Nat_acc_{t-2}	—	0.11 (0.15)	0.22 (0.27)	0.44 (0.49)
$Gstar_{t-2}$	—	−0.10 (0.15)	0.07 (0.29)	0.17 (0.64)
Ex_rate_{t-3}	—	—	0.11 (0.28)	0.19 (0.48)
Pr_index_{t-3}	—	—	−0.15 (0.39)	0.02 (0.52)
$Hfood\_pr_{t-3}$	—	—	−0.14 (0.31)	0.28 (0.58)
Int_rate_{t-3}	—	—	−0.39 (0.69)	−0.72 (0.99)
$Credit_{t-3}$	—	—	0.20 (0.31)	0.14 (0.73)
Nat_acc_{t-3}	—	—	−0.07 (0.22)	−0.09 (0.39)
$Gstar_{t-3}$	—	—	−0.13 (0.20)	−0.19 (0.48)
Ex_rate_{t-4}	—	—	—	−0.03 (0.42)
Pr_index_{t-4}	—	—	—	−0.24 (0.57)
$Hfood\_pr_{t-4}$	—	—	—	−0.32 (0.42)
Int_rate_{t-4}	—	—	—	0.89 (1.20)
$Credit_{t-4}$	—	—	—	0.05 (0.47)
Nat_acc_{t-4}	—	—	—	0.04 (0.30)
$Gstar_{t-4}$	—	—	—	−0.15 (0.33)

Note: Numbers in brackets are standard errors in the posterior distribution.
The dimension of the dependent variable decreases from 42 (one lag) to 39 (four lags).

Table 3.9: WALS estimates for Model 2 (Inflation), Version 2

	One lag	Two lags	Three lags	Four lags
Focus regressors				
Intercept	0.93 (0.34)	0.06 (0.62)	0.09 (0.91)	−0.73 (1.86)
INF_{t-1}	0.22 (0.28)	0.66 (0.40)	0.29 (0.72)	0.48 (1.46)
Ex_rate_{t-1}	0.17 (0.15)	0.00 (0.21)	0.10 (0.30)	−0.05 (0.45)
Pr_index_{t-1}	0.42 (0.23)	0.24 (0.29)	0.43 (0.47)	0.46 (0.85)
$Hfood\_pr_{t-1}$	−0.04 (0.21)	−0.38 (0.29)	−0.21 (0.43)	−0.46 (0.86)
INF_{t-2}	—	0.28 (0.31)	0.48 (0.62)	0.88 (1.20)
Ex_rate_{t-2}	—	−0.03 (0.19)	−0.14 (0.33)	0.06 (0.53)
Pr_index_{t-2}	—	−0.35 (0.29)	−0.25 (0.38)	−0.57 (0.66)
$Hfood\_pr_{t-2}$	—	−0.20 (0.26)	−0.28 (0.48)	−0.68 (0.86)
INF_{t-3}	—	—	0.14 (0.47)	−0.50 (0.86)
Ex_rate_{t-3}	—	—	0.13 (0.30)	0.19 (0.51)
Pr_index_{t-3}	—	—	−0.31 (0.43)	−0.04 (0.57)
$Hfood\_pr_{t-3}$	—	—	−0.29 (0.35)	0.21 (0.62)
INF_{t-4}	—	—	—	0.77 (0.76)
Ex_rate_{t-4}	—	—	—	0.01 (0.44)
Pr_index_{t-4}	—	—	—	−0.41 (0.61)
$Hfood\_pr_{t-4}$	—	—	—	−0.48 (0.47)
Auxiliary regressors				
Int_rate_{t-1}	−0.06 (0.12)	0.28 (0.45)	0.20 (0.70)	0.59 (0.92)
$Credit_{t-1}$	0.08 (0.11)	−0.24 (0.22)	−0.19 (0.38)	−0.01 (0.53)
Nat_acc_{t-1}	−0.04 (0.13)	0.11 (0.19)	0.07 (0.27)	0.12 (0.36)
$Gstar_{t-1}$	−0.16 (0.11)	0.04 (0.19)	0.05 (0.34)	0.21 (0.55)
Int_rate_{t-2}	—	−0.30 (0.43)	0.10 (0.75)	−0.57 (1.35)
$Credit_{t-2}$	—	0.28 (0.20)	0.00 (0.46)	0.10 (0.94)
Nat_acc_{t-2}	—	0.11 (0.15)	0.21 (0.27)	0.44 (0.49)
$Gstar_{t-2}$	—	−0.09 (0.15)	0.07 (0.29)	0.17 (0.64)
Int_rate_{t-3}	—	—	−0.39 (0.69)	−0.74 (0.99)
$Credit_{t-3}$	—	—	0.20 (0.31)	0.14 (0.75)
Nat_acc_{t-3}	—	—	−0.06 (0.22)	−0.10 (0.39)
$Gstar_{t-3}$	—	—	−0.13 (0.20)	−0.19 (0.49)
Int_rate_{t-4}	—	—	—	0.89 (1.20)
$Credit_{t-4}$	—	—	—	0.06 (0.47)
Nat_acc_{t-4}	—	—	—	0.03 (0.30)
$Gstar_{t-4}$	—	—	—	−0.15 (0.33)

Note: Numbers in brackets are standard errors in the posterior distribution.
The dimension of the dependent variable decreases from 42 (one lag) to 39 (four lags).

fluctuations in Armenia are autocorrelated. It appears that *Ex_rate* dynamics are positively correlated with inflation, due to the fact that Armenia is a small open economy with an imports-to-GDP ratio of about 40%. The home price index therefore depends strongly on the international price index level.

Finally, let us compare Table 3.6 with Table 3.7, and Table 3.8 with Table 3.9. The difference between the tables is that there are fewer focus variables in Table 3.6 (version 1) than in Table 3.7 (version 2), and similarly, fewer focus variables in Table 3.8 than in Table 3.9. A comparison between the results tells us that the estimates are generally of the same sign and size. Concerning the standard errors two remarkable findings emerge. First, the standard error of a parameter is generally higher when the parameter is a focus parameter than when it is treated as an auxiliary parameter. For example, the parameter corresponding to $Invest_{t-1}$ in the one-lag model has standard error 0.41 in version 1, and 0.46 in version 2. Second, when there are more focus variables, the standard errors of the parameters corresponding to auxiliary variables (such as $Gstar_{t-1}$) become (slightly) smaller. These findings appear to be quite general and robust. The second result is quite intuitive: more things are fixed (more focus variables) and hence the standard errors become smaller. But the first result is puzzling and potentially important: if we treat a variable as auxiliary while it should be treated as focus, then we obtain standard errors that are misleadingly small, leading to too much confidence in our results.

3.7 An estimation simulation experiment

While the previous results are of practical and theoretical interest, a proper comparison between WALS and BMA can only be done through a simulation experiment, where we know the data-generating process (DGP) and can therefore relate the estimates to the truth. The DGP that we have chosen follows closely the models estimated in the previous section. We conduct the simulation experiments for one, two, and three lags, so that we gain insight on the performance of the WALS and BMA algorithms for various lag lengths. In Tables 3.10 and 3.11 we present the parameter values in the data-generating processes for the growth and inflation models, respectively.

Table 3.10: Data-generation process, Model 1 (Growth), Version 2

	One lag	Two lags	Three lags
Intercept	0.50	1.20	3.00
G_{t-1}	0.75	0.95	0.80
$Invest_{t-1}$	−0.30	−0.70	−0.40
$ImpExp_{t-1}$	−0.15	0.00	0.10
Nat_acc_{t-1}	0.60	0.15	0.55
Mon_agg_{t-1}	0.30	0.40	0.40
Pr_index_{t-1}	0.20	0.35	0.30
$Gstar_{t-1}$	−0.35	0.10	−0.30
G_{t-2}	—	−0.60	−1.30
$Invest_{t-2}$	—	0.30	1.30
$ImpExp_{t-2}$	—	0.30	0.40
Nat_acc_{t-2}	—	0.95	1.15
Mon_agg_{t-2}	—	0.40	0.70
Pr_index_{t-2}	—	−0.25	0.90
$Gstar_{t-2}$	—	0.05	0.90
G_{t-3}	—	—	−0.10
$Invest_{t-3}$	—	—	0.75
$ImpExp_{t-3}$	—	—	0.45
Nat_acc_{t-3}	—	—	0.60
Mon_agg_{t-3}	—	—	0.90
Pr_index_{t-3}	—	—	−0.30
$Gstar_{t-3}$	—	—	−0.30
σ^2	2.25	2.25	2.25

We randomly draw the $\{\epsilon_t\}$ from a standard-normal distribution. Then, given the data-generating process and the values of the regressors, we generate the time series for real GDP growth or inflation, the dependent variables. Now that we have all the data, we estimate the parameters using the models and the estimation algorithms of Section 3.6. This gives us parameter estimates. Next we draw new errors $\{\epsilon_t\}$, obtain new values for the dependent variable, and hence new parameter estimates. We repeat this 1000 times, and compute

Table 3.11: Data-generation process for Model 2 (Inflation), Version 2

	One lag	Two lags	Three lags
Intercept	1.00	0.10	−2.00
INF_{t-1}	0.10	0.80	1.40
Ex_rate_{t-1}	0.20	0.60	−0.10
Pr_index_{t-1}	0.55	−0.15	−0.15
$Hfood\_pr_{t-1}$	0.10	−0.15	−0.85
Int_rate_{t-1}	−0.20	0.00	0.50
$Credit_{t-1}$	0.10	−0.55	−0.50
Nat_acc_{t-1}	−0.10	−0.70	0.70
$Gstar_{t-1}$	−0.30	−0.40	0.40
INF_{t-2}	—	0.50	1.00
Ex_rate_{t-2}	—	−0.50	−0.15
Pr_index_{t-2}	—	−0.50	−0.75
$Hfood\_pr_{t-2}$	—	0.40	−0.50
Int_rate_{t-2}	—	0.50	0.60
$Credit_{t-2}$	—	0.40	0.60
Nat_acc_{t-2}	—	0.40	0.80
$Gstar_{t-2}$	—	0.40	0.40
INF_{t-3}	—	—	0.30
Ex_rate_{t-3}	—	—	0.25
Pr_index_{t-3}	—	—	−0.65
$Hfood\_pr_{t-3}$	—	—	−0.20
Int_rate_{t-3}	—	—	−0.50
$Credit_{t-3}$	—	—	0.60
Nat_acc_{t-3}	—	—	−0.50
$Gstar_{t-3}$	—	—	0.50
σ^2	1.44	1.44	1.44

the simulation root mean squared errors (RMSE):

$$\text{RMSE}_k^{wals} = \sqrt{\frac{1}{1000}\sum_{l=1}^{1000}(\beta_k^{wals_l} - \beta_k^{true})^2},$$

$$\text{RMSE}_k^{bma} = \sqrt{\frac{1}{1000}\sum_{l=1}^{1000}(\beta_k^{bma_l} - \beta_k^{true})^2},$$

where β_k^{true} denotes the true value of β_k, and $\beta_k^{wals_l}$ and $\beta_k^{bma_l}$ are the corresponding WALS and BMA estimates, respectively, for the l-th iteration.

Table 3.12: RMSE for estimation simulations, Model 1 (Growth), Version 2

	WALS	BMA	WALS	BMA	WALS	BMA
Intercept	0.0373	0.0375	0.0293	0.0270	0.0330	0.0399
G_{t-1}	0.0192	0.0193	0.0292	0.0283	0.0247	0.0222
$Invest_{t-1}$	0.0340	0.0341	0.0366	0.0362	0.0212	0.0216
$ImpExp_{t-1}$	0.0129	0.0130	0.0116	0.0118	0.0101	0.0099
Nat_acc_{t-1}	0.0172	0.0173	0.0190	0.0199	0.0132	0.0122
Mon_agg_{t-1}	0.0164	0.0206	0.0142	0.0151	0.0134	0.0180
Pr_index_{t-1}	0.0099	0.0110	0.0100	0.0124	0.0104	0.0119
$Gstar_{t-1}$	0.0154	0.0126	0.0132	0.0064	0.0202	0.0148
G_{t-2}	—	—	0.0163	0.0170	0.0380	0.0395
$Invest_{t-2}$	—	—	0.0146	0.0141	0.0480	0.0516
$ImpExp_{t-2}$	—	—	0.0092	0.0099	0.0113	0.0119
Nat_acc_{t-2}	—	—	0.0105	0.0109	0.0161	0.0171
Mon_agg_{t-2}	—	—	0.0082	0.0098	0.0150	0.0194
Pr_index_{t-2}	—	—	0.0097	0.0088	0.0259	0.0259
$Gstar_{t-2}$	—	—	0.0124	0.0065	0.0254	0.0288
G_{t-3}	—	—	—	—	0.0056	0.0053
$Invest_{t-3}$	—	—	—	—	0.0263	0.0244
$ImpExp_{t-3}$	—	—	—	—	0.0124	0.0134
Nat_acc_{t-3}	—	—	—	—	0.0138	0.0140
Mon_agg_{t-3}	—	—	—	—	0.0161	0.0202
Pr_index_{t-3}	—	—	—	—	0.0104	0.0087
$Gstar_{t-3}$	—	—	—	—	0.0109	0.0088

The results of the Monte-Carlo simulations are presented in Tables 3.12 (for growth) and 3.13 (for inflation). The main purpose of these simulations is to compare BMA and WALS. WALS has certain theoretical and computational advantages, but does it in fact perform better than BMA? The simulations suggest that this might be the case, although the difference is small. In the growth simulations, WALS achieves a lower RMSE than BMA for 88% (one lag), 53% (two lags), and 61% (three lags) of the parameters, thus outperforming BMA. In the inflation simulations, the percentages are somewhat

Table 3.13: RMSE for estimation simulations, Model 2 (Inflation), Version 2

	WALS	BMA	WALS	BMA	WALS	BMA
Intercept	0.0095	0.0089	0.0529	0.0538	0.0882	0.0910
INF_{t-1}	0.0067	0.0062	0.0261	0.0257	0.0409	0.0416
Ex_rate_{t-1}	0.0061	0.0061	0.0126	0.0124	0.0174	0.0180
Pr_index_{t-1}	0.0065	0.0065	0.0161	0.0163	0.0269	0.0252
$Hfood\_pr_{t-1}$	0.0067	0.0067	0.0200	0.0216	0.0341	0.0354
Int_rate_{t-1}	0.0052	0.0057	0.0197	0.0184	0.0455	0.0253
$Credit_{t-1}$	0.0047	0.0038	0.0138	0.0163	0.0210	0.0202
Nat_acc_{t-1}	0.0046	0.0038	0.0117	0.0138	0.0198	0.0209
$Gstar_{t-1}$	0.0052	0.0070	0.0101	0.0127	0.0171	0.0123
INF_{t-2}	—	—	0.0195	0.0204	0.0341	0.0351
Ex_rate_{t-2}	—	—	0.0093	0.0073	0.0127	0.0107
Pr_index_{t-2}	—	—	0.0189	0.0187	0.0297	0.0318
$Hfood\_pr_{t-2}$	—	—	0.0127	0.0120	0.0210	0.0215
Int_rate_{t-2}	—	—	0.0169	0.0135	0.0318	0.0252
$Credit_{t-2}$	—	—	0.0115	0.0127	0.0164	0.0132
Nat_acc_{t-2}	—	—	0.0089	0.0092	0.0185	0.0224
$Gstar_{t-2}$	—	—	0.0064	0.0092	0.0120	0.0108
INF_{t-3}	—	—	—	—	0.0111	0.0105
Ex_rate_{t-3}	—	—	—	—	0.0117	0.0084
Pr_index_{t-3}	—	—	—	—	0.0134	0.0108
$Hfood\_pr_{t-3}$	—	—	—	—	0.0115	0.0115
Int_rate_{t-3}	—	—	—	—	0.0289	0.0176
$Credit_{t-3}$	—	—	—	—	0.0161	0.0161
Nat_acc_{t-3}	—	—	—	—	0.0084	0.0124
$Gstar_{t-3}$	—	—	—	—	0.0097	0.0106

lower: 39% (one lag), 59% (two lags), and 48% (three lags). Hence, a slight advantage for WALS over BMA.

The above estimation simulations were based on the assumption that the data-generation process and the model coincide. For example, if the DGP has one lag, then we use a model with one lag. This, of course, is not realistic, since in practice we don't know the DGP and therefore the chance that our chosen model happens to be the DGP is negligible. We now consider one case where the model is underspecified. More specifically, the DGP has three lags,

Table 3.14: RMSE for estimation simulations in the case of misspecification, Models 1 and 2, Version 2

Growth			Inflation		
	WALS	BMA		WALS	BMA
Intercept	0.0297	0.0302	*Intercept*	0.0520	0.0513
G_{t-1}	0.0201	0.0202	INF_{t-1}	0.0442	0.0437
$Invest_{t-1}$	0.0356	0.0357	Ex_rate_{t-1}	0.0154	0.0153
$ImpExp_{t-1}$	0.0131	0.0132	Pr_index_{t-1}	0.0297	0.0297
Nat_acc_{t-1}	0.0181	0.0182	$Hfood\_pr_{t-1}$	0.0263	0.0264
Mon_agg_{t-1}	0.0175	0.0223	Int_rate_{t-1}	0.0107	0.0127
Pr_index_{t-1}	0.0103	0.0121	$Credit_{t-1}$	0.0101	0.0123
$Gstar_{t-1}$	0.0162	0.0121	Nat_acc_{t-1}	0.0167	0.0188
			$Gstar_{t-1}$	0.0107	0.0115

but the model has only one lag. We estimate the parameters in the one-lag model and compare with the corresponding (true) parameters in the three-lag DGP. The results are presented in Table 3.14. Here, also, WALS appears to be at an advantage. For 88% (growth) and 61% (inflation) of the parameters, WALS achieves a lower RMSE than BMA.

3.8 A forecast experiment

We conduct a second experiment, this time in forecasting rather than estimation. Suppose we use $T_1 < T = 43$ quarters on which we base our estimates. This leaves us $T_2 = T - T_1 > 0$ quarters for forecast experiments. The h-period forecast is given by

$$\hat{y}_{T_1+h} = \hat{\alpha}(L) y_{T_1+h-1} + \hat{\gamma}(L) f_{T_1+h-1} \qquad (h = 1, \ldots, T_2),$$

where y denotes either GDP growth or inflation. In a practical situation we would not know f_{T_1+h-1} and y_{T_1+h-1}, when $h \geq 2$. So we would have to forecast these as well. In the experiment we use the observed values of f_{T_1+h-1} and y_{T_1+h-1}, hence not the forecasted value $\hat{y}_{T_1+h-1}$ when $h \geq 2$. Then we compute

$$\mathrm{RMSE}_{T_1} = \sqrt{\frac{1}{T - T_1} \sum_{h=1}^{T-T_1} (\hat{y}_{T_1+h} - y_{T_1+h})^2},$$

which depends on the estimation period T_1, the model, and the method (BMA or WALS). The results are presented in Tables 3.15 and 3.16.

Table 3.15: RMSE for ex-post forecast accuracy, Model 1 (Growth)

			T_1				
Number of lags	Version	Method	38	37	36	35	34
One lag	1	WALS	0.8557	0.9967	2.5503	6.1158	3.6533
		BMA	0.8338	0.9726	2.4993	6.3675	3.5549
		GtS	0.9606	1.1124	2.6739	6.0492	3.4711
		OLS	0.9847	1.0726	3.2020	5.6782	3.6570
	2	WALS	0.8597	1.0181	2.8576	5.8070	3.6330
		BMA	0.9416	1.1265	2.5818	5.9392	3.6009
		GtS	1.1311	1.2979	2.3720	6.0667	3.5998
		OLS	0.9847	1.0726	3.2020	5.6782	3.6570
Two lags	1	WALS	2.2203	2.8415	3.6176	2.7037	2.6341
		BMA	1.8333	2.3204	3.2558	2.4816	1.7849
		GtS	2.0147	2.9072	3.1916	2.4471	1.5800
		OLS	2.6610	3.3104	3.5279	3.2889	3.2062
	2	WALS	2.2162	2.8118	3.5271	3.1048	2.7043
		BMA	2.2155	2.6711	3.6429	3.0343	2.5689
		GtS	2.9367	3.4904	3.7139	3.1051	2.8986
		OLS	2.6610	3.3104	3.5279	3.2889	3.2062
Three lags	1	WALS	2.3276	2.5872	4.3087	4.5578	2.8051
		BMA	2.1199	1.9616	3.2988	3.8783	3.0844
		GtS	2.0535	2.5983	4.1221	4.5073	3.5460
		OLS	2.5757	3.1871	4.4612	4.9230	3.1832
	2	WALS	2.2043	2.7098	4.1208	4.6082	3.2474
		BMA	2.1169	2.8038	4.2715	4.6699	3.6258
		GtS	2.8060	1.5199	3.8202	4.4603	4.3567
		OLS	2.5757	3.1871	4.4612	4.9230	3.1832

Table 3.16: RMSE for ex-post forecast accuracy, Model 2 (Inflation)

			T_1				
Number of lags	Version	Method	38	37	36	35	34
One lag	1	WALS	0.8542	0.7807	0.9050	0.8545	0.8993
		BMA	0.8851	0.8810	0.9949	0.9373	0.9697
		GtS	0.9906	1.0484	1.0819	1.0232	1.0198
		OLS	0.9060	0.8448	0.8741	0.8788	0.8842
	2	WALS	0.8923	0.8061	0.9000	0.8813	0.8865
		BMA	0.9579	0.8718	0.9787	0.9291	0.9421
		GtS	1.0024	0.9252	1.0051	0.9481	0.9559
		OLS	0.9060	0.8448	0.8741	0.8788	0.8842
Two lags	1	WALS	1.6452	1.6568	1.5987	1.7970	1.5262
		BMA	1.0726	0.9829	0.8997	1.0536	0.9385
		GtS	1.0536	0.9371	0.7445	1.0959	0.8920
		OLS	2.0139	2.1006	2.0722	2.3070	1.8852
	2	WALS	1.6357	1.6463	1.5935	1.7557	1.5967
		BMA	1.1079	1.0094	1.0292	1.1293	1.3293
		GtS	1.0076	0.9035	1.0614	1.1510	1.2761
		OLS	2.0139	2.1006	2.0722	2.3070	1.8852
Three lags	1	WALS	4.5016	3.8276	4.1335	3.9527	2.7138
		BMA	1.2269	1.1040	1.0326	0.9662	1.1329
		GtS	6.1520	1.1017	4.7159	4.7402	4.5196
		OLS	6.1409	5.2268	5.7689	5.4534	3.5626
	2	WALS	4.2447	3.4789	3.9977	3.8076	2.4278
		BMA	1.3646	1.2628	1.3900	1.2499	1.9155
		GtS	0.9806	1.0851	2.0882	1.9551	1.7758
		OLS	6.1409	5.2268	5.7689	5.4534	3.5626

In this case we have calculated the RMSE not only for BMA and WALS, but also for two traditional methods of estimation: general-to-specific (GtS) model selection followed by estimation of the selected model, and ordinary least squares (OLS) of the unrestricted model. Including these standard forecasting methods allows us to compare model averaging with more traditional methods.

For all cases, the smaller is the estimation period T_1, the less accurate are the estimates and the forecasts, that is, the RMSE increases as T_1 decreases. This is to be expected and it happens most of the time, but not always. In particular the behavior for $T_1 = 35$ is different. The explanation lies in the global financial crisis, which affected Armenia heavily. From the third quarter of 2008 (quarter 34 in our data set) to the second quarter of 2009 (quarter 37) Armenia's GDP decreased by 18%. The largest decrease (around 9.0%) in real GDP took place in the fourth quarter of 2008 (quarter 35). Such a large decrease in real GDP causes a large deviation of real GDP from its long-term trend, and this explains (in part) why the RMSE values calculated for $T_1 = 35$ are relatively large, and for $T_1 = 36$ somewhat smaller.

Two main conclusions emerge from Tables 3.15 and 3.16. First, we see that the model averaging techniques WALS and BMA outperform the more traditional methods GtS and OLS. But the choice between WALS and BMA is still ambiguous. While in the estimation simulations we found that WALS performs better than BMA, we find in the forecasting simulations that BMA performs better than WALS in 2/3 of the 30 forecasts, both for growth and for inflation.

3.9 Concluding remarks

We have applied two alternative model averaging algorithms (WALS and BMA) to the problem of estimating factor-based dynamic models in Armenia. The same models are also used to forecast two key macroeconomic variables, namely real GDP growth and inflation. The theoretical advantage of using model averaging is that it allows all models to play a role in the estimation and forecasting, thus avoiding the problem of pretesting. A comparison of the WALS to the BMA algorithm does not reveal large differences in performance. The WALS methodology has a stronger theoretical appeal, but — in the current context — there is not sufficient evidence to prefer one over the other. The simulations do show, however, that both model averaging methods outperform the more traditional methods (general-to-specific and OLS).

3.10 Appendix: List of 42 initial macroeconomic variables

A. National accounts

1. *GDP*: Gross domestic product at average annual prices of 2005, mln drams
2. *Cons*: Final consumption expenditure at average annual prices of 2005, mln drams
3. *Inv*: Gross capital formation at average annual prices of 2005, mln drams
4. *Exp*: Export at annual average prices of 2005, mln drams
5. *Imp*: Import at annual average prices of 2005, mln drams
6. *Ind*: Value added of industry at average annual prices of 2005, mln drams
7. *Agr*: Value added of agriculture, hunting and forestry, fishing at average annual prices of 2005, mln drams
8. *Cstr*: Value added of construction at annual average prices of 2005, mln drams
9. *Serv*: Value added of services at average annual prices of 2005, mln drams

B. Prices and exchange rates

1. *CPI*: Consumer price index with respect to the previous period (%)
2. $Food_{pr}$: Food stuff price index, end of current period with respect to the end of previous period (%)
3. $NFood_{pr}$: Nonfood stuff price index, end of current period with respect to the end of previous period (%)

4. $Serv_{pr}$: Price index of services payable, end of current period with respect to the end of previous period (%)

5. $Wheat_{pr}$: Wheat price index with respect to the previous period (%)

6. $Fuel_{pr}$: Fuel price index with respect to the previous period (%)

7. $Food_{pr}^{imp}$: Imported food price index with respect to the previous period (%)

8. $NFood_{pr}^{imp}$: Imported non-food price index with respect to the previous period (%)

9. $HFood_{pr}^{imp}$: Home food price index with respect to the previous period (%)

10. $Regul_{pr}$: Administrative regulated price index with respect to the previous period (%)

11. Exr_{usd}^{amd}: Exchange rate US dollars per Armenian's dram, period average

12. Exr_{euro}^{amd}: Exchange rate EU Euro per Armenian's dram, period average

13. Exr_{rr}^{amd}: Exchange rate Russian ruble per Armenian's dram, period average

C. Financial and monetary policy indicators

1. *Cash*: Money in circulation, mln drams, end of period

2. *M0*: Monetary base, mln drams, end of period

3. *M1*: Includes currency in circulation and demand deposits (including accounts) and borrowings in drams, end of period

4. *M2X*: Broad money, includes currency in circulation and demand deposits (including accounts) and borrowings in drams and foreign currency, end of period

5. *Dep*: Total deposits in the banking system, mln drams, end of period

6. $Cred$: Total credit to economy, mln drams, end of period
7. $Cred_{firm}$: Credit to enterprises, mln drams, end of period
8. $Cred_{house}$: Credit to households, mln drams, end of period
9. Dep^{d}_{ir}: Deposits interest rate in local currency (%)
10. Dep^{f}_{ir}: Deposits interest rate in US dollars (%)
11. $Cred^{d}_{ir}$: Local currency loans interest rate (%)
12. $Cred^{f}_{ir}$: US dollars loans interest rate (%)
13. CB_{inter}: Central bank interbank interest rate (%)

D. International indicators

1. US_{gdp}: US real GDP growth rate with respect to the previous period (%)
2. EU_{gdp}: EU real GDP growth rate with respect to the previous period (%)
3. US^{def}_{gdp}: US GDP deflator with respect to the previous period (%)
4. EU^{def}_{gdp}: EU GDP deflator with respect to the previous period (%)
5. Gas_{pr}: International price index for gasoline with respect to the previous period (%)
6. $Petrol_{pr}$: International price index for petroleum with respect to the previous period (%)
7. $Wheat_{pr}$: International price index for wheat with respect to the previous period (%)

Chapter 4

Factor model versus DSGE model: An out-of-sample forecast comparison

Factor model versus DSGE model: An out-of-sample forecast comparison*

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Abstract: Two approaches for modeling and forecasting macroeconomic time series are compared: a dynamic factor model (DFM) and a theory-based dynamic stochastic general equilibrium (DSGE) model. We estimate the two models for the Armenian economy using quarterly macroeconomic time series from 2000 to 2010. We compare the accuracy of the resulting forecasts using out-of-sample data, and we conclude that DFMs outperform DSGE models in terms of forecast accuracy for the Armenian economy. We also test the common belief that DFMs should be used for short-term forecasting, while DSGE models should be used for the long term. We find that DFMs are suitable for both short- and long-term forecasting, while DSGE models seem to perform better only for long-run forecasts.

4.1 Introduction

In order to conduct effective monetary policy, practitioners from Central Banks are interested in producing accurate forecasts of the relevant economic variables. Traditional forecasting models include univariate autoregressive (AR) and vector autoregression (VAR) models. But these models can not accommodate a large number of time series, so that potentially important information is lost. This is why, in the last decades, methods that reduce dimensionality, such as factor models, have gained importance for macroeconomic prediction.

There are two factor models that are frequently used in applications, described in Stock and Watson (2002) and Forni et al. (2000), respectively. Both

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models are based on principal component analysis, but the first model is static while the second model is dynamic. The two factor models have the same purpose, namely, given a large number of initial variables, to extract only a small number of factors which summarize the information contained in the whole data set. There are many applications of factor models to forecasting macroeconomic and financial variables (Forni et al., 2000; Stock and Watson, 2002; Artis et al., 2002; Schneider and Spitzer, 2004; Matheson, 2006; and Schumacher, 2007). The main finding of these applications is that the forecasts generated from factor models are superior to traditional univariate and multivariate time-series models.

A second approach for modeling and forecasting which has become popular over the last few decades, is the dynamic stochastic general equilibrium (DSGE) model. DSGE models were developed for analyzing the transmission channels mainly for monetary policy under various random shocks. In recent years, the DSGE model has also been used for economic forecasting. For example, Smets and Wouters (2004) estimated a medium-scale DSGE model in a Bayesian framework, and argued that their model is able to generate superior forecasts relative to an unrestricted VAR.

Thus two opposite macroeconomic forecasting approaches emerged: the DSGE model, with a strong economic background, and the factor-based dynamic model, which is mainly data-driven. The main purpose of this chapter is to compare the two models and to see which forecasting approach produces more accurate forecasts. At the moment the literature provides only a few comparisons between DSGE and factor-model forecasting methods. Some papers carry out an out-of-sample forecasting experiment between the DSGE and the factor model. For example, Wang (2009) pointed out that the factor model outperforms the DSGE model when the period is short, but that for long periods the DSGE model performs better. Gupta and Kabundi (2008) conducted short-period forecasts and also concluded that the factor model outperforms the DSGE model in the short run. Another interesting comparison of DSGE versus DFM is provided by Wieland (2010).

These results are informative, but they do not automatically hold for other economies, since they are based on country-specific data. In particular, results from developed economies do not necessarily hold for developing economies. Our application is to Armenia, and our research question is how the two models compare in their forecasting performance for this particular country. We also investigate whether, for Armenia, the factor-based model should be used mainly for the short-term while the DSGE model should be used mainly for long-term forecasts. In addition, we investigate another prevailing hypothesis according to which the factor-based model is superior to simple AR models, while the DSGE model is superior to standard unrestricted VAR models. We find that the DFM is in general superior to the DSGE model in terms of its forecasting performance for Armenia. We also find that the DSGE model is better suited to longer-run predictions for the Armenian economy. Our findings for the Armenian economy correspond closely to those of related papers, such as Wang (2009) and Gupta and Kabundi (2008). The results should be of interest both for researchers in the field of forecasting and for policy makers from Central Banks.

The chapter is organized as follows. The factor model is described in Section 4.2. In Section 4.3 we describe a simple DSGE model for a small open economy. The dataset used for factor-based and DSGE model estimation and forecasting is presented in Section 4.4. Section 4.5 presents the recursive and rolling regression schemes for our experimental design. In Section 4.6 we present out-of-sample forecasts and forecast comparisons. Section 4.7 concludes.

4.2 Factor model

In recent years, factor models are widely used in Central Banks mainly for producing short-term forecasts. As a rule, the factor models can be constructed in two steps: factor extraction, followed by model estimation and forecasting. In the literature there are three main algorithms for extracting factors, namely static and dynamic principal component analysis and the so-called subspace algorithm. In the current chapter, we use Stock and Watson's (2002) approach (static principal component analysis) to derive factors. This is the most widely applied approach.

To determine the factors following the Stock-Watson approach, we proceed as follows (see also Schumacher, 2007). We start with a collection of stationary $N \times 1$ time-series vectors x_t,

$$x_t = (x_{1t}, x_{2t}, \ldots, x_{Nt})' \qquad (t = 1, 2, \ldots, T).$$

Let

$$\hat{\Gamma}_0 = \frac{1}{T} \sum_{t=1}^{T} x_t x_t'$$

be an estimate of the variance matrix of the initial set of variables. The aim is to find r linear combinations of the time-series data

$$f_{i,t} = \hat{s}_i' x_t \qquad (i = 1, 2, \ldots, r)$$

that maximize the variance of the factors $\hat{s}_i' \hat{\Gamma}_0 \hat{s}_i$. Imposing the usual restriction that $\hat{s}_i' \hat{s}_i = 1$ and solving the optimization problem, we find the matrix equation

$$\hat{\Gamma}_0 \hat{s}_i = \hat{\mu}_i \hat{s}_i,$$

so that $\hat{\mu}_i$ denotes the i-th eigenvalue of $\hat{\Gamma}_0$ and $\hat{s}_i$ the $N \times 1$ corresponding eigenvector. Thus, in order to estimate the principal components we need to find the eigenvalues and eigenvectors of $\hat{\Gamma}_0$, the variance matrix of the initial data. The number of extracted factors should be relatively small compared to N, but the extracted factors should also be sufficient to explain most of the variation in the initial variables. According to the static principal component approach the r eigenvectors corresponding to the first r largest eigenvalues are the weights of the static factors.

Having extracted the factors we move to the estimation and forecasting step. The forecasting model has the form (Stock and Watson, 2002; Koop and Potter, 2004):

$$y_{t+h} = \alpha(L) y_t + \beta(L) \hat{f}_t + \epsilon_{t+h} \tag{4.1}$$

where $\hat{f}_t$ $(m \times 1)$ is the vector of extracted principal components, $\beta(L)$ is a polynomial in the lag operator, and $h = 1, 2, \ldots$ is the forecasting horizon. The autoregressive term is accounted for by the coefficient $\alpha(L)$. We assume that $r < N$ and $r < T$. The estimated factor-based model is then used to compute forecasts for selected time series.

In a number of applications (Stock and Watson, 2002; Schumacher, 2007; Kunovach, 2007), Equation (4.1) is estimated by ordinary least squares (OLS). However, as shown in Koop and Potter (2004) and Poghosyan and Magnus (2012), factor-based dynamic models are better estimated using model averaging algorithms than traditional estimation methods (general-to-specific and OLS). The theoretical advantage of model averaging is that it properly combines model selection and estimation into *one* procedure, thus avoiding the undesirable problem of pretesting. The WALS methodology (introduced in Magnus et al., 2010) has a stronger theoretical appeal than traditional Bayesian model averaging (BMA), but in the context of forecasting there is not sufficient evidence to prefer one over the other. Therefore, for forecasting purposes we will use both model averaging algorithms (WALS and BMA). In Magnus et al. (2010) and De Luca and Magnus (2011) the computational algorithms of BMA and WALS are presented in detail.

4.3 DSGE model

Following Berg et al. (2006), we consider four key behavioral equations: aggregate demand (IS curve), aggregate supply (Phillips curve), real exchange rate (uncovered interest rate parity), and a monetary policy rule (reaction function):

$$
\begin{aligned}
y_t &= \mu E_t y_{t+1} + (1-\mu) y_{t-1} - \phi r_t + \kappa e_t + \epsilon_{y,t}, \\
\pi_t &= \delta E_t \pi_{t+1} + (1-\delta)\pi_{t-1} + \lambda y_t + \tau(e_t - e_{t-1}) + \epsilon_{\pi,t}, \\
e_t &= \varphi E_t e_{t+1} + (1-\varphi) e_{t-1} - \eta(r_t - r_t^*) + \epsilon_{e,t}, \\
i_t &= \rho i_{t-1} + (1-\rho)[\beta E_t \pi_{t+1} + \gamma y_t] + \epsilon_{i,t}.
\end{aligned}
$$

All variables are in log-deviations from their steady-state values, that is in gap terms. Thus, y_t is the output gap, π_t is the inflation gap, e_t is the real exchange rate gap, and i_t is the nominal interest rate gap. In addition,

$$r_t = i_t - E_t\pi_{t+1}, \qquad r_t^* = i_t^* - E_t\pi_{t+1}^*,$$

where r_t^* denotes the international interest rate. The error terms denote shocks: $\epsilon_{y,t}$ is an aggregate demand shock with mean zero and variance σ_y^2; $\epsilon_{\pi,t}$ is an aggregate supply shock with mean zero and variance σ_π^2; $\epsilon_{e,t}$ is a real exchange rate shock with mean zero and variance σ_e^2; and $\epsilon_{i,t}$ is a nominal interest rate shock with mean zero and variance σ_i^2.

The first equation gives aggregate demand (IS curve). The output gap is a function of its past and future values, and the equation includes the real interest rate and the real exchange rate. The influence of monetary policy is effected via changes in the real interest rate and the real exchange rate. The second equation gives aggregate supply (Phillips curve). Inflation in our model has both a backward-looking and a forward-looking component. Higher values of δ imply greater importance of the forward-looking component, and lower values indicate dominance of the backward-looking component. The coefficient on the output gap reflects the trade-off between inflation and output, and is expected to be positive. The equation also includes the first difference of the real exchange rate gap, whose coefficient we expect to be positive. The third equation reflects a form of partial uncovered interest parity. The exchange rate dynamics imposed by this equation depend on the difference between home and foreign interest rate. When this difference is positive, the exchange rate is expected to depreciate in the long run, and vice versa. The final equation formulates the interest rate reaction function of monetary policy makers. It is expressed as a weighted sum of an autoregressive term and the Central Bank policy rule. The autoregressive nature reflects conservative behavior of the Central Bank. If inflation is higher than the target level, then policy makers will increase the interest rate, which will have a negative effect on the output gap thus bringing inflation closer to its target level.

Most papers consider structural estimation or reduced-form estimation separately but not jointly. In this chapter we combine the two estimation procedures and we use both of them contemporaneously. For the estimation of the DSGE model parameters, we use iterated GMM rather than calibration to pre-estimate some parameters that are usually considered nuisance parameters in DSGE models. We then fix these nuisance parameters at their pre-estimated values and perform IRF matching estimation for the parameters of interest: see Poghosyan and Boldea (2012) for further details of the procedure.

4.4 Data and descriptive statistics

Our dataset consist of quarterly time series of 42 macroeconomic variables from 2000:Q2 to 2010:Q4, in total 43 observations for each variable. The data are collected from the Central Bank of Armenia, the National Statistical Agency (NSA), and International Financial Statistics (IFS). The set comprises information on national accounts data (9 variables), prices and exchange rates (11 variables), labor market indicators (5 variables), financial and monetary policy indicators (11 variables), and international indicators (7 variables). The complete set of Armenian macroeconomic time series variables is presented in the Appendix. All time series are in natural logarithms, except for the interest rate which is measured in percentage points. Stationarity is obtained by appropriate detrending of the time series, and seasonal fluctuations are eliminated by using the TRAMO/SEATS seasonal adjustment methodology, if necessary. To eliminate the scale effect, the series are centered and scaled, so that they have zero mean and unit variance.

Our purpose is to conduct out-of-sample forecasting experiments using both the factor and the DSGE model. Using these models, we then forecast the dynamics of four key macroeconomic indicators: real GDP, inflation, the real exchange rate, and nominal interest rate dynamics. Let us first define these four target variables. Real GDP is defined as the quarterly growth rate of the seasonally adjusted real GDP (in % of the previous quarter); inflation is the quarterly change (growth or decline in % of the previous quarter) of the consumer price index (CPI); the real exchange rate is the change (growth or decline in % of the previous quarter) of the Armenian drams per US dollar; and the nominal interest rate is the Central Bank policy nominal interest rate on repurchase operations, in percentage points. We start the forecasting period in the first quarter of 2008, and forecast up to the fourth quarter of 2010. This implies that we use eight years to estimate various models, and that the remaining two years of observations are used for out-of-sample forecast assessment.

FIGURES 4.1–4.4

The dynamics of the four key variables are presented in Figures 4.1–4.4. The 2008 global economic and financial crisis led to a sharp decrease in real GDP in the fourth quarter of 2008 and the first quarter of 2009 (Figure 4.1). In 2009 compared to 2008 real GDP declined by about 15%, but starting from 2010 the growth of real GDP is again positive. Inflation has responded less dramatically during the global financial crisis (Figure 4.2). The exchange rate and policy nominal interest rate have not changed significantly during the global economic crisis (Figures 4.3 and 4.4).

In this chapter we estimate and forecast factor-based dynamic models using principal components. For determining the principal components we use static principal component analysis with varimax rotation. We used 42 initial macroeconomic time series (excluding all dependent variables, that is, real GDP, inflation, exchange rate, and interest rate). The extracted principal components have been given names based on the correlation coefficients between the extracted principal components and the initial set of macroeconomic time series. Some important characteristics of the extracted factors are presented in Table 4.1.

TABLE 4.1

We see from Table 4.1 that 11 principal components have been extracted. A factor is included if the rotated eigenvalue is larger than one. The first principal component, which we believe to be related to the exchange rate and therefore denoted by Ex_rate, contributes 13.54% to the total variance of the initial variable; the second component, potentially related to investment variables, is called $Invest$ and explains 9.97% of the variance; the third component, related to the interest rate and denoted by Int_rate, explains 9.32% of the initial variance. We see that the 11 extracted factors explain over 80% of the variance of the initial set of variables, which we take to be sufficient for describing the information in the initial dataset.

TABLE 4.2

Table 4.2 provides the correlations between the extracted factors and the four key macroeconomic indicators. The factors most highly correlated with the real GDP growth rate are $Invest$, Nat_acc, Mon_agg, and Ex_rate. All these factors are positively correlated with real GDP growth rate, because they are all highly correlated with the gross investment and construction growth rates. The last two variables are important ingredients for describing the real GDP growth rate. Inflation is positively correlated with Ex_rate and $Food\_prx$, which is reasonable given that $Food\_prx$ is related to food and non-food price indexes. The next two macroeconomic indicators, the real exchange rate (EXR) and policy interest rate (PIR), are correlated with the factors Ex_rate and Int_rate, respectively.

For making proper comparisons with the AR model, we choose a specification similar to Koop and Potter (2004), and hence we take as our focus variables only lagged values of the dependent variables, while all extracted factors are considered auxiliary. In order to be able to make comparisons with the DSGE model, we need to include in the factor-based model only one lag, because our DSGE model includes only one lag. Our conclusions regarding the forecasting ability of the DSGE model are based on comparisons with the unrestricted VAR model.

FIGURES 4.5–4.8

For the estimation of the DSGE model equations we will use quarterly dynamics of the four key macroeconomic time series: real GDP, inflation, real exchange rate, and interest rate. But for estimating the DSGE model, in contrast to the factor model, all these time series should be in gap terms. The variables have been detrended using the Hodrick-Prescott (HP) filter, and the resulting plots are presented in Figures 4.5–4.8. Since the solution of the DSGE model can be approximated by a restricted VAR model, it is reasonable to estimate a corresponding unrestricted VAR model as an alternative procedure for an out-of-sample forecasting experiment. The unrestricted VAR contains the same observed variables as the restricted VAR obtained from a DSGE model: that is, real GDP, inflation, the real exchange rate, and the nominal interest rate set by policy makers.

4.5 Experimental design

To conduct out-of-sample forecast experiments, we use both recursive and rolling regressions. The in-sample data period spans 2000:Q2 to 2007:Q4 (31 observations, almost eight years), while the out-of-sample period is 2008:Q1–2010:Q4 (12 observations, three years).

The recursive simulation scheme proceeds as follows: First, we estimate the models using subsample 2000:Q2–2007:Q4 (31 observations) and generate 1 to 8 steps-ahead forecasts. Then, we increase the sample size by one (32 observations) and generate again 1 to 8 steps-ahead forecasts. We continue increasing the sample size by one and generating 1 to 8 steps-ahead forecasts until the sample size is 35. Then we increase the sample size by one (36 observations), but only generate 1 to 7 steps-ahead forecasts (since we only have 43 observations in total). We continue increasing the sample size until we have 42 observations in the sample, in which case we can only compute the 1-step-ahead forecast. In this way we obtain twelve 1-step-ahead forecasts, eleven 2-steps-ahead forecasts, and eventually five 8-steps-ahead forecasts.

While in the recursive scheme the sample size increases by one quarter at each step, in the rolling regressions we fix the sample size at 31 observations. As in the recursive regression case the forecast horizon is 1–8 quarters. The first estimation sample starts in 2000:Q2 and ends in 2007:Q4 so that the forecasting quarters are 2008:Q1–2009:Q4. The second sample starts in 2000:Q3 and ends in 2008:Q1, with forecasting quarters are 2008:Q2–2010:Q1. The fifth sample starts in 2001:Q2 and ends in 2008:Q4, with forecasting quarters are 2009:Q1–2010:Q4. We continue in this way until the twelfth sample (2003:Q1–2010:Q3), but the forecasting quarters then decrease with each sample since we have no observations after 2010:Q4.

The number of forecasts is the same in both methods. The recursive scheme has the advantage of using all the data available at a certain point in time, but the rolling forecast scheme is useful if a structural change occurs in the sample (Schumacher, 2007).

Next, we use the out-of-sample forecasts from both recursive and rolling regressions to compute the corresponding root mean squared errors (RMSE) for each of the eight forecasting horizons. More specifically, let us denote the out-of-sample period by T^* (in our case, $T^* = 12$, namely 2008:Q1–2010:Q4), and the forecast horizon by h ($h = 1, 2, \ldots, 8$). Then the RMSE is calculated from

$$\mathrm{RMSE}_{ih} = \sqrt{\frac{1}{T^* - (h-1)} \sum_{t=1}^{T^*-(h-1)} (\hat{y}_{it} - y_{it})^2},$$

where y_{it} denotes the actual value of the i-th dependent variable (in our case we have four dependent variables and therefore $i = 1, 2, 3, 4$), $\hat{y}_{it}$ is the forecasted value of the i-th dependent variable, and RMSE_{ih} is the root mean squared error calculated for the i-th dependent variable and the h-th forecast horizon.

Since all macroeconomic variables included in the DSGE model are known, the solution of the DSGE model can be approximated by a restricted VAR model. Thus, we forecast in the same way as a traditional unrestricted VAR model, except that we use predicted values of the endogenous regressors in generating the forecasts.

4.6 Forecast results

We now compare and discuss the 1–8 out-of-sample RMSEs of the factor model versus DSGE model.

TABLES 4.3 and 4.4

We see from Tables 4.3 and 4.4 that the RMSEs calculated for the VAR are typically lower than the corresponding values calculated for the DSGE forecasting model. The DFM forecasts are, in most cases, more accurate than those generated from an AR model. From the RMSEs, we also conclude that for the interest rate, the AR model outperforms the DFM, possibly because of a large backward-looking (autoregressive) component. However, for the three other key macroeconomic indicators (real GDP growth, inflation, exchange rate), the forecasts obtained by factor-based models are typically more accurate.

We also find that traditional VAR forecasts outperform structural DSGE model forecasts. There is no evidence therefore, at least from the Armenian data, that DSGE forecasts are more reliable than unrestricted VAR forecasts. The factor models estimated by WALS and BMA always outperform the DSGE in terms of RMSEs. Hence, based on Armenian macroeconomic data, we reject the prevailing hypothesis that the factor model should be used mainly for producing short-horizon forecasts, while the DSGE model should be used for long-horizon forecasts. In fact, factor models can be used effectively both for short-term and for long-term forecasts.

In order to evaluate the model's forecast accuracy, we perform across-model tests between the benchmark DFM with the VAR and DSGE models. The across-model test is based on a statistic proposed by Diebold and Mariano (1995). Let ϵ_t^i ($i = \text{VAR}, \text{DSGE}$) denote the forecast errors from the alternative models, and let ϵ_t^d denote the forecast errors from the factor models. The Diebold-Mariano (DM) statistic is then defined as

$$s = l/\sigma_l,$$

where l is the sample mean of the loss $l_t = (\epsilon_t^i)^2 - (\epsilon_t^d)^2$, and σ_l is the standard error of l. The DM-statistic is asymptotically distributed as a standard normal random variable and it can be estimated under the null hypothesis of equal forecast accuracy, that is $l = 0$. If $s > 0$ then DFM outperforms the alternative model (VAR or DSGE) and vice versa; if $s < 0$ then the alternative model outperforms DFM.

TABLES 4.5–4.8

The DM statistics presented in Tables 4.5–4.8 allow us to try and reject the hypothesis that two different models generate the same forecasts. If the DM statistic is larger (in absolute value) than some critical value (say 1.96 at the 95% level), then we reject the null hypothesis and conclude that the two models or forecasting schemes are different in the sense that they produce statistically different forecasts.

In Table 4.5 we compare the DFM_wals method with both the unrestricted VAR model and the DSGE model using the recursive scheme. The comparison DFM_wals with VAR yields 12 significant results (out of 32), particularly for the policy interest rate (6/8). The comparison DFM_wals with DSGE yields 14 significant results (out of 32), particularly for inflation (8/8).

In Table 4.6 we compare the DFM_bma method with both the unrestricted VAR model and the DSGE model, again using the recursive scheme. The comparison DFM_bma with VAR now yields 13 significant results, again particularly for the policy interest rate (6/8), and the comparison DFM_bma with DSGE yields 10 significant results, again particularly for inflation (8/8). With less than 40% of the cases significant, we cannot conclude that the models produce different forecasts, neither for WALS nor for BMA.

The situation is different in the rolling scheme reported in Tables 4.7 and 4.8. Here we find that the DFM method produces quite different forecasts than DSGE, particularly when WALS is used but also with BMA. We find 27/32 significant DM values for WALS and 21/32 for BMA. Based on these comparisons we conclude that the differences in the produced forecasts are particularly strong between the DFM and the DSGE models.

4.7 Conclusion

In this chapter we compared two popular forecasting models, DFM and DSGE, using out-of-sample recursive forecast simulations. For the estimation of the factor model we used ten extracted factors; for the estimation of the DSGE model only four key macroeconomic variables. The estimated factor and DSGE models were used to forecast real GDP, inflation, exchange rate, and policy interest rate. The four models were evaluated based on the RMSE criterium for 1–8 quarters-ahead forecast horizons. The results show that the estimated factor-based model performs better than the DSGE model in forecasting the four key macroeconomic variables. There is no evidence to support the popular belief that factor models should be used for short-term forecasting and DSGE models for long-term forecasting. The simulation experiments using actual macroeconomic time series show that factor models can be used both for short-term and for long-term period forecasting, while the DSGE model is more accurate for long-term forecasting.

4.8 Appendix A: Macroeconomics variables

National accounts:

1. (GDP) gross domestic product at average annual prices of 2005, mln. drams
2. ($Cons$) final consumption at average annual prices of 2005, mln. drams
3. (Inv) gross capital formation at average annual prices of 2005, mln. drams
4. (Exp) export at average annual prices of 2005, mln. drams
5. (Imp) import at average annual prices of 2005, mln. drams
6. (Ind) value added of industry at average annual prices of 2005, mln. drams
7. (Agr) value added of agriculture at average annual prices of 2005, mln. drams
8. ($Cstr$) value added of construction at average annual prices of 2005, mln. drams
9. ($Serv$) value added of services at average annual prices of 2005, mln. drams

Prices and exchange rates:

1. (CPI) consumer price index with respect to the previous period (%)
2. ($Food_{pr}$) Food stuff price index, end of current period over the end of previous period (%)
3. ($NFood_{pr}$) Non-food stuff price index, end of current period over the end of previous period (%)
4. ($Serv_{pr}$) Price index of services payable, end of current period over the end of previous period (%)

5. ($Wheat_{pr}$) wheat price index with respect to the previous period (%)

6. ($Fuel_{pr}$) fuel price index with respect to the previous period (%)

7. ($Food_{pr}^{imp}$) imported food price index with respect to the previous period (%)

8. ($NFood_{pr}^{imp}$) imported non-food price index with respect to the previous period (%)

9. ($HFood_{pr}^{imp}$) home food price index with respect to the previous period (%)

10. (Exr_{usd}^{amd}) exchange rate US dollars per armenian's dram, period average

11. (Exr_{euro}^{amd}) exchange rate EU Euro per armenian's dram, period average

12. (Exr_{rr}^{amd}) exchange rate Russian ruble per armenian's dram, period average

Labor market:

1. (N_e) labor force ths. people

2. (N_t) Economically active labor force, ths. people

3. (N_{un}) unemployed, ths. people

4. ($Prod$) productivity, per employee

5. (W) Average monthly nominal wages, drams

Financial and monetary policy indicators:

1. ($Cash$) money in circulation, mln. drams, end of period

2. ($M0$) monetary base, mln. drams, end of period

3. ($M1$) includes currency in circulation and demand deposits (including accounts) and borrowings in drams, end of period

4. ($M2X$) is broad money, includes currency in circulation and demand deposits (including accounts) and borrowings in drams and foreign currency, end of period

5. (Dep) total deposits in the banking system, mln. drams, end of period

6. ($Cred$) total credit to economy, mln. drams, end of period

7. (Dep_{ir}^{d}) deposits interest rate in local currency (%)

8. (Dep_{ir}^{f}) deposits interest rate in US dollars (%)

9. ($Cred_{ir}^{d}$) local currency loans interest rate (%)

10. ($Cred_{ir}^{f}$) US dollars loans interest rate (%)

11. (CB_{inter}) Central Bank interbank interest rate (%)

International indicators:

1. (US_{gdp}), US real GDP growth rate with respect to the previous period (%)

2. (EU_{gdp}), EU real GDP growth rate with respect to the previous period (%)

3. (US_{gdp}^{def}), US GDP deflator with respect to the previous period (%)

4. (EU_{gdp}^{def}), EU GDP deflator with respect to the previous period (%)

5. (Gas_{pr}) international price index for gasoline with respect to the previous period (%)

6. ($Petrol_{pr}$) international price index for petroleum with respect to the previous period (%)

7. ($Wheat_{pr}$) international price index for wheat with respect to the previous period (%)

4.9 Appendix B: Tables

Table 4.1: Characteristics of the extracted principal components

Principal components	Rotated eigenvalues	% of total variance	Cumulative variance in %
Ex_rate	5.69	13.54	13.54
Invest	4.19	9.97	23.51
Int_rate	3.92	9.32	32.83
Mon_agg	3.47	8.27	41.10
ImpExp	3.06	7.30	48.40
Lforce	2.91	6.93	55.33
Nat_acc	2.76	6.56	61.90
Wage	2.74	6.52	68.42
Food_prx	2.32	5.52	73.94
Cstr_prx	1.69	4.02	77.97
Trsprt_prx	1.60	3.81	81.77

Table 4.2: Correlation coefficients between extracted factors and key macroeconomic variables

Factors	GDP	INF	EXR	PIR
Ex_rate	0.19	0.33	0.62	−0.02
Invest	0.72	0.07	−0.37	−0.08
Int_rate	0.06	−0.15	0.29	0.89
Mon_agg	0.26	−0.05	−0.25	−0.09
ImpExp	0.17	−0.12	−0.13	0.11
Lforce	−0.20	0.17	−0.11	−0.12
Nat_acc	0.32	−0.15	−0.13	−0.08
Wage	0.14	−0.20	−0.14	0.06
Food_prx	0.18	0.72	−0.24	0.05
Cstr_prx	0.10	−0.12	−0.14	−0.02
Trsprt_prx	0.01	0.06	0.05	−0.03

Table 4.3: RMSE (2008/Q1–2010/Q4): Recursive scheme

	1	2	3	4	5	6	7	8
Real GDP								
DFM_wals	1.81	2.05	2.31	2.10	1.68	2.04	0.98	2.84
DFM_bma	2.08	2.26	2.07	2.15	1.81	1.82	1.12	2.26
AR	1.99	1.83	2.08	2.18	1.72	1.86	1.48	1.64
VAR	2.21	1.76	2.21	2.26	1.57	1.96	1.55	1.66
DSGE	3.10	3.94	5.04	4.55	2.90	2.60	1.06	4.23
Inflation								
DFM_wals	1.12	1.02	1.34	1.30	1.30	1.55	1.18	2.45
DFM_bma	1.23	1.04	1.00	1.08	0.94	1.07	0.80	1.08
AR	1.19	0.96	1.00	1.03	0.96	1.00	0.86	0.91
VAR	1.56	1.32	1.84	1.46	1.40	1.15	1.20	0.85
DSGE	3.51	5.77	6.45	6.84	7.55	8.65	11.44	12.35
Exchange rate								
DFM_wals	0.86	1.16	1.75	1.43	2.68	2.92	3.12	2.23
DFM_bma	1.12	1.08	1.39	1.96	2.13	1.90	2.86	1.84
AR	1.30	1.43	1.63	1.70	1.92	1.77	0.78	0.80
VAR	2.57	0.99	2.23	1.81	2.24	1.92	0.89	0.98
DSGE	1.44	2.07	2.16	2.35	1.95	2.11	1.57	2.34
Interest rate								
DFM_wals	0.39	0.91	0.87	1.23	1.30	1.43	1.38	1.31
DFM_bma	0.24	0.97	0.84	0.96	1.07	1.44	1.27	0.77
AR	0.16	0.26	0.32	0.33	0.29	0.18	0.09	0.11
VAR	0.27	0.33	0.46	0.38	0.36	0.20	0.11	0.13
DSGE	0.16	0.21	0.44	0.69	0.94	1.21	1.50	1.78

Table 4.4: RMSE (2008/Q1–2010/Q4): Rolling scheme

	1	2	3	4	5	6	7	8
Real GDP								
DFM_wals	1.71	2.13	2.13	1.99	1.71	2.06	0.92	2.77
DFM_bma	1.79	2.28	2.23	2.20	2.00	1.88	1.41	2.13
AR	1.98	1.84	2.08	2.19	1.72	1.87	1.48	1.65
VAR	2.20	1.76	2.24	2.28	1.57	1.97	1.61	1.68
DSGE	5.47	20.22	8.98	6.80	3.21	9.30	1.30	2.07
Inflation								
DFM_wals	1.23	0.98	1.27	1.34	1.43	1.61	1.20	2.10
DFM_bma	1.22	1.03	1.01	1.07	1.20	1.27	0.77	1.03
AR	1.14	0.95	0.98	1.03	0.95	1.00	0.86	0.91
VAR	1.43	1.23	1.77	1.46	1.42	1.20	1.27	0.84
DSGE	5.26	19.47	9.86	8.52	9.64	18.31	5.17	6.10
Exchange rate								
DFM_wals	0.70	1.09	1.63	1.57	2.86	2.91	3.16	2.49
DFM_bma	1.16	1.31	1.34	1.83	2.10	2.15	2.15	1.02
AR	1.33	1.45	1.65	1.72	1.95	1.78	0.78	0.79
VAR	3.22	1.14	2.68	1.90	2.42	1.91	0.96	0.98
DSGE	2.57	4.72	4.40	3.25	1.91	4.85	0.55	1.10
Interest rate								
DFM_wals	0.33	0.67	1.00	1.38	1.67	1.98	2.17	1.81
DFM_bma	0.17	0.58	0.60	0.79	0.96	1.27	1.37	0.96
AR	0.17	0.26	0.32	0.32	0.29	0.21	0.18	0.20
VAR	0.30	0.33	0.39	0.42	0.42	0.33	0.25	0.26
DSGE	0.15	0.63	0.42	0.54	0.65	0.99	0.66	0.85

Table 4.5: DM statistics (2008/Q1–2010/Q4): Recursive scheme

	1	2	3	4	5	6	7	8
Real GDP: DFM_wals versus								
VAR	0.73	−0.63	−0.19	0.31	−0.22	−0.17	0.92	−3.21*
DSGE	2.04*	2.87*	3.98*	3.59*	1.93	0.99	0.14	1.66
Inflation: DFM_wals versus								
VAR	0.73	0.18	0.70	−0.14	0.06	0.24	−0.97	−6.21*
DSGE	3.14*	5.51*	6.13*	6.50*	7.30*	8.52*	11.21*	11.86*
Exchange rate: DFM_wals versus								
VAR	2.28*	−0.38	0.85	0.67	−0.97	−2.51*	−10.06*	−4.11*
DSGE	0.92	1.42	0.74	1.48	−1.74	−1.93	−4.63*	0.22
Policy interest rate: DFM_wals versus								
VAR	−0.28	−2.15*	−1.18	−3.56*	−4.27*	−10.08*	−17.89*	−12.70*
DSGE	−0.80	−3.84*	−1.29	−1.52	−0.86	−0.48	0.23	0.82

* Significant at 5% level

Table 4.6: DM statistics (2008/Q1–2010/Q4): Recursive scheme

	1	2	3	4	5	6	7	8
Real GDP: DFM_bma versus								
VAR	2.04*	2.87*	3.98*	3.59*	1.93	0.99	0.14	1.66
DSGE	−0.60	−0.41	0.00	−0.02	−0.19	−1.15	−1.44	−0.78
Inflation: DFM_bma versus								
VAR	0.59	0.51	1.30	0.67	0.77	0.16	0.67	−0.51
DSGE	3.08*	5.58*	6.30*	6.68*	7.43*	8.51*	11.38*	12.26*
Exchange rate: DFM_bma versus								
VAR	2.09*	−0.19	1.36	−0.32	0.21	0.05	−8.29*	−2.48*
DSGE	0.57	1.51	1.27	0.72	−0.38	0.40	−3.63*	0.90
Policy interest rate: DFM_bma versus								
VAR	0.05	−2.46*	−1.08	−2.02*	−2.76*	−10.31*	−15.12*	−4.29*
DSGE	−0.22	−4.34*	−1.19	−0.65	−0.27	−0.52	0.43	1.45

* Significant at 5% level

Table 4.7: DM statistics (2008/Q1–2010/Q4): Rolling scheme

	1	2	3	4	5	6	7	8
Real GDP: DFM_wals versus								
VAR	0.87	−0.82	0.22	0.53	−0.29	−0.18	1.09	−2.91*
DSGE	4.94*	20.00*	8.47*	6.22*	2.30*	8.84*	0.65	−1.64
Inflation: DFM_wals versus								
VAR	0.37	0.44	0.86	0.24	−0.01	−0.98	0.13	−4.41*
DSGE	4.97*	19.42*	9.70*	8.31*	9.43*	18.16*	4.89*	5.37*
Exchange rate: DFM_wals versus								
VAR	3.07*	0.09	1.69	0.60	−0.98	−2.55*	−9.51*	-5.34*
DSGE	2.38*	4.47*	3.80*	2.49*	-2.40*	3.10*	−17.60*	−4.54*
Policy interest rate: DFM_wals versus								
VAR	−0.05	−1.01	−2.16*	−4.08*	−6.17*	−11.54*	−18.84*	-12.22*
DSGE	−0.56	−0.08	−1.94	−2.98*	−3.61*	−2.95*	−6.48*	−3.02 *

* Significant at 5% level

Table 4.8: DM statistics (2008/Q1–2010/Q4): Rolling scheme

	1	2	3	4	5	6	7	8
Real GDP: DFM_bma versus								
VAR	0.75	−1.21	0.03	0.16	−0.97	0.18	0.38	−1.03
DSGE	4.89*	19.97*	8.43*	6.09*	1.96*	8.92*	−0.23	−0.11
Inflation: DFM_bma versus								
VAR	0.39	0.36	1.19	0.69	0.41	−0.14	0.81	−0.43
DSGE	4.98*	19.42*	9.76*	8.38*	9.49*	18.22*	5.05*	5.93*
Exchange rate: DFM_bma versus								
VAR	2.81*	−0.37	2.01*	0.14	0.59	−0.51	−3.88*	−0.09
DSGE	2.04*	4.36*	3.99*	2.21*	−0.41	3.90*	−7.85*	0.14
Policy interest rate: DFM_bma versus								
VAR	0.20	−0.68	−0.53	−1.04	−1.77	−4.61*	−7.40*	−3.22*
DSGE	−0.05	0.09	−0.43	−0.61	−0.76	−0.65	−2.20*	−0.23

* Significant at 5% level

4.10 Appendix C: Figures

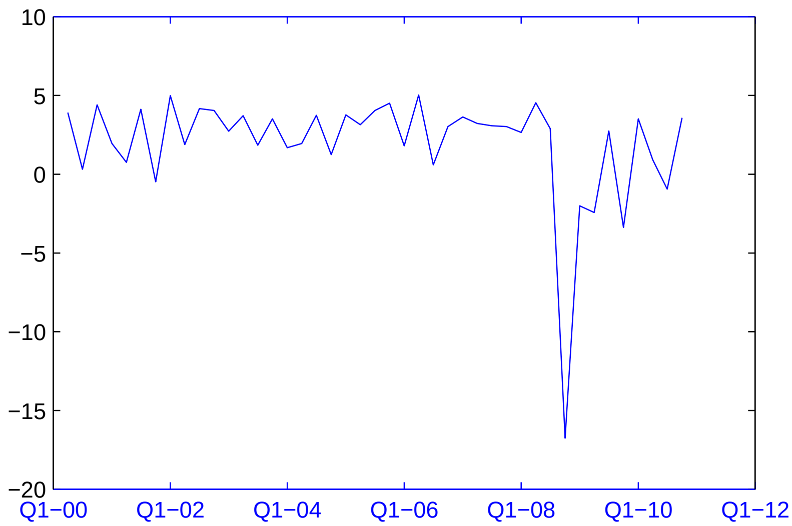

Figure 4.1: Quarterly growth rate of real GDP, 2000/Q2–2010/Q4

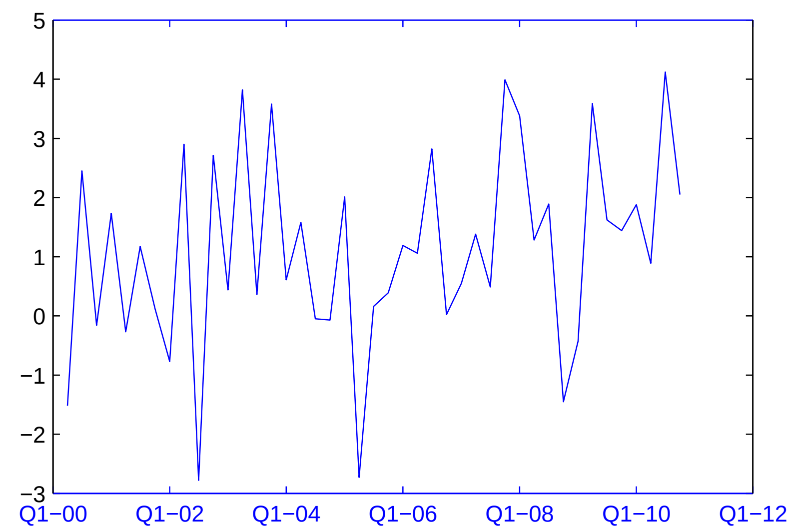

Figure 4.2: Inflation (quarterly growth rate of CPI), 2000/Q2–2010/Q4

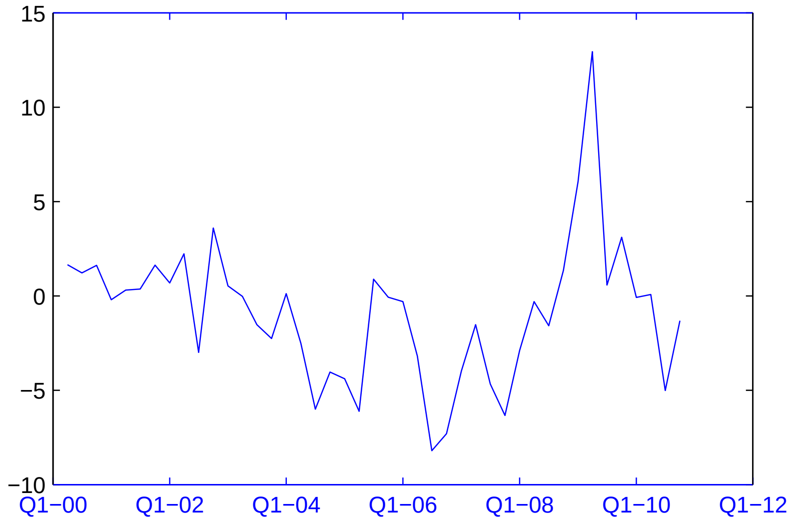

Figure 4.3: Real exchange rate (quarterly growth rate of Armenian's dram per US dollar), 2000/Q2–2010/Q4

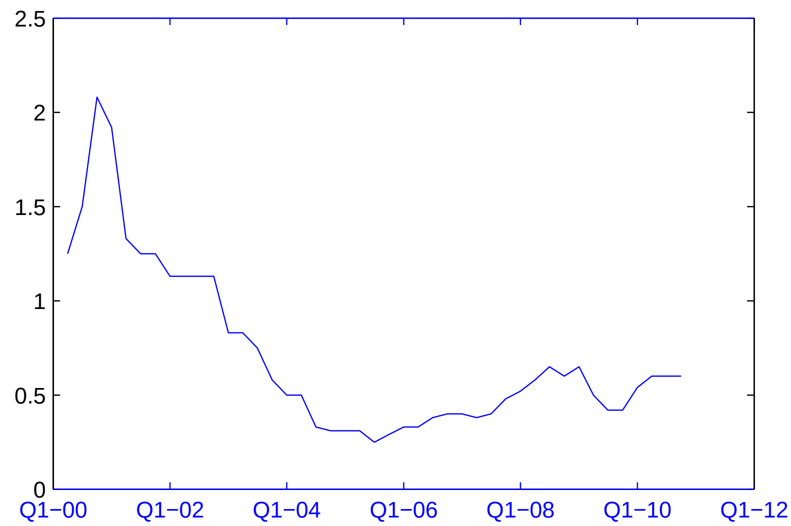

Figure 4.4: Central Bank policy nominal interest rate, 2000/Q2–2010/Q4

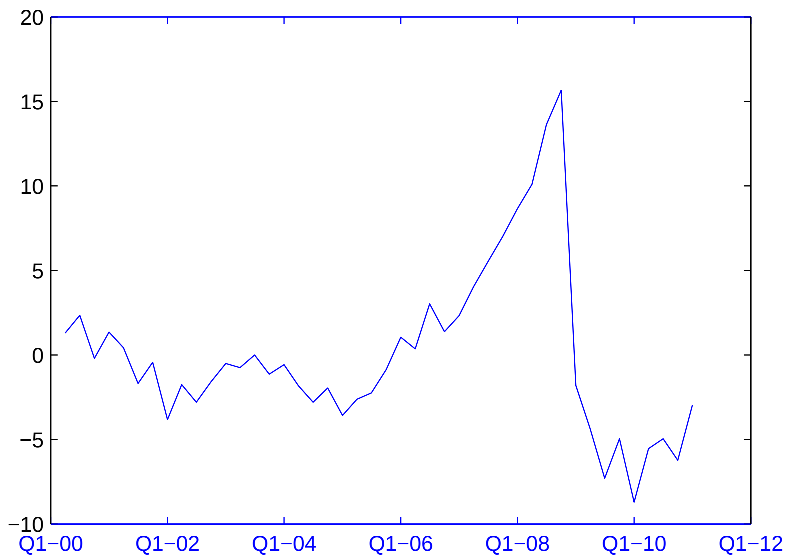

Figure 4.5: Output gap, 2000/Q1–2010/Q4

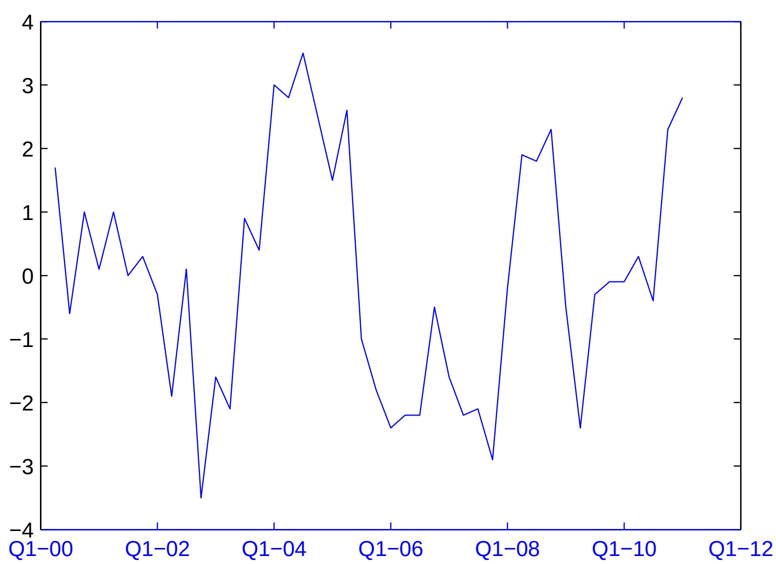

Figure 4.6: Inflation gap, 2000/Q1–2010/Q4

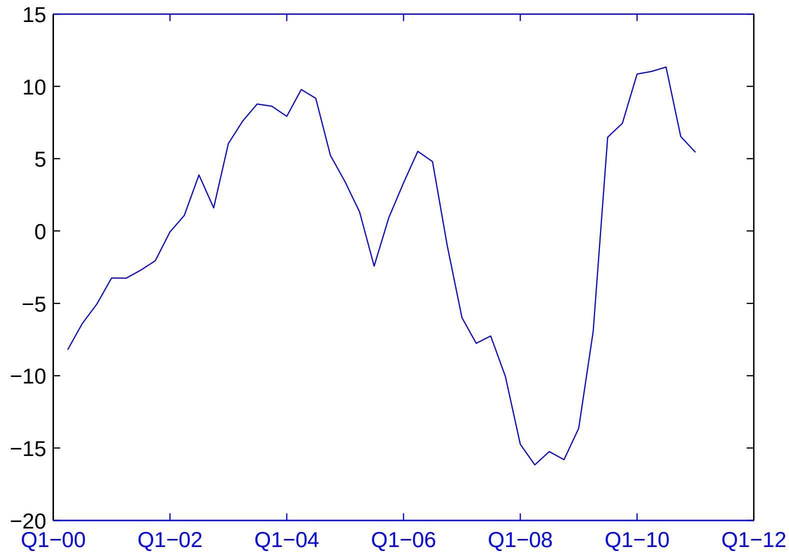

Figure 4.7: Real exchange rate gap, 2000/Q1–2010/Q4

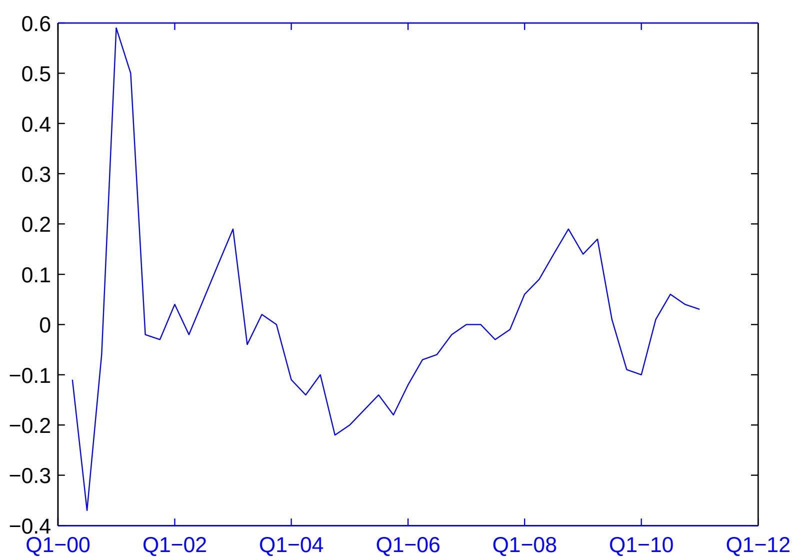

Figure 4.8: Central Bank policy interest rate gap, 2000/Q1–2010/Q4

Summary

The main purpose of the current thesis is to compare structural and reduced-form models for estimating and forecasting the dynamics of key macroeconomic variables. To achieve this purpose we conduct a comparative analysis, first within and then between various types of forecasting models. The main idea of conducting the within-models comparisons is that using various estimation methods we try to find those methods which gives better forecasting results. The main idea of conducting between-models comparisons is that we try to find the appropriate type of model that gives more accurate forecasts comparing with other types of models. All three chapters of the thesis are closely related to this purpose. In the first two chapters we make comparisons within the same type of forecasting models, while in the last chapter we compare various types of forecasting models, particularly the factor and the DSGE model. The thesis thus attempts to make an empirical contribution to macroeconomic time-series modeling and forecasting. The chapters are briefly summarized as follows.

In Chapter 2 we show that using both structural and reduced-form estimates simultaneously can lead to more accurate policy predictions. Our main finding is that structural GMM estimation and reduced-form minimum distance estimation (MDE) methods can be used simultaneously for estimating structural small-scale DSGE models. In addition, we show how to use the recently developed information criteria (Hall et al., 2012) for selection valid and relevant impulse responses. Misspecification in the structural model or using too many impulse responses can lead to biased estimates and inaccurate policy conclusions. By using the proposed information criteria it is possible to pick such impulse responses that not only provide a more reliable estimator, but also indicate valid and relevant portions of the model, where validity and relevance refers to accurate description of the transmission of shocks into the economy.

In Chapter 3 we analyze a reduced-form forecasting model, particularly the factor-based dynamic model. We apply two alternative model-averaging

algorithms, BMA and WALS, to the problem of estimating factor-based dynamic modes in Armenia. The theoretical advantage of using model averaging is that it allows us to combine model selection and estimation into one procedure, thus avoiding the undesirable problem of pretesting. A comparison of WALS and BMA does not reveal large differences in forecasting performances. The WALS method has a stronger theoretical appeal, but within the forecasting framework there is no strong evidence to prefer one method over the other. The ex-post simulation experiments, however, indicate that both model averaging algorithms outperform more traditional methods (general-to-specific and OLS).

In Chapter 4 we compare the factor model with the DSGE model. In this chapter we try to check the prevailing hypothesis according to which a factor model should be used for short period forecasts, while a DSGE model should be used for long period forecasts. The ex-post forecast experiments show that there is no strong evidence to support this hypothesis. The simulation experiments using Armenian's actual quarterly macroeconomic time series show that factor model can be used both for short- and long period forecasts, while the DSGE model is better used for long period forecasts.

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